IMPROVING VISION IMPAIRED USERS ACCESS TO ELECTRONIC RESOURCES IN E-LEARNING ENVIRONMENT WITH MODIFIED ARTIFICIAL NEURAL NETWORK

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CERTIFICATION

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ABSTRACT

Assistive Technology (ATs) provide means through which persons with visual impairment are empowered with adaptive devices and methods for accessing multimedia information. However, the degree of sensitivity and specificity values for access to electronic resources by visual impaired persons varies. Existing ATs were designed as “one model fits all” (static calibration requirements), thereby limiting the usability by vision impaired users in an e-learning environment. The study presents a Dynamic Thresholding Model (DTM) that adaptively adjusts the vision parameters to meet the calibration requirements of vision impaired users.

Data from International Statistical Classification of Diseases and Related Health Problems of World Health Organisation (WHO) containing 1001 instances of visual impairment measures were obtained from 2008 to 2013. The users’ vision parameters of WHO for Visual Acuity Range (VAR) were adopted. These were: VAR $\geq$ 0.3(299); 0.1 $<$ VAR $<$ 0.3(182); 0.07 $\leq$ VAR $<$ 0.1(364); 0.05 $\leq$ VAR $<$ 0.07(120); 0.02 $\leq$ VAR $<$ 0.05(24); and VAR $<$ 0.02(12). Data for six VAR groups were partitioned into 70% (700) and 30% (301) for training and testing, respectively. Data for the six groups were transformed into 3-bits encoding to facilitate model derivation. The DTM was developed with calibrator parameters (Visual Acuity (*Va*), Print Size (*Ps*) and Reading Rate (*Rr*)) for low acuity, adaptive vision calibrator and dynamic thresholding. The VAR from the developed DTM was used to predict the optimal operating range and accuracy value on observed WHO dataset irrespective of the grouping. Six-epochs were conducted for each thresholding value to determine the sensitivity and specificity values relative to the False Negative Rate (FNR) and False Positive Rate (FPR), respectively, which are evidences of misclassification.

The 3-bit encoding coupled with the DTM yielded optimised equations of the form:

$$OP1 = 463.6073Ps - 597.0703Va + 573.8042Rr$$
$$OP2 = 1.9383Ps - 1.7474Va + 0.4508Rr$$
$$OP3 = 8.4985Va - 1.2436Ps - 17.1718Rr.$$

Where OP1, OP2 and OP3 represent the first, second and third bit, respectively. Five local maxima accuracy and one global maximum threshold values were obtained from the DTM. Local maxima threshold values were 0.455, 0.470, 0.515, 0.530, and 0.580, with corresponding percentage accuracy of 99.257, 99.343, 99.171, 99.229, and 99.429. Global maximum accuracy was 99.6 at threshold value of 0.5. The *Va*, *Ps*, and *Rr* produced equal numbers of observations (301) agreeing with the result in WHO report. Correctly classified user impairment was 99.89%, with error rate of 0.11%. The model predicted sensitivity value of 99.79% (0.21 FNR), and specificity value of 99.52% (0.48 FPR).

The developed dynamic thresholding model adaptively classified various degrees of visual impairment for vision impaired users.

Keywords: Visual acuity, Visual print size, Assistive technology, Vision impaired reading rate

Word count: 410

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ABBREVIATIONS

ANN	Artificial Neural Network
AR	Acuity Reserve
BDA	Best Distance Acuity
CPS	Critical Print Size
DA	Distance Acuity
DAL	Desired Acuity Level
DVA	Distance Visual Acuity
EVD	Equivalent Viewing Distance
LVA	Low Vision Aids
NVA	Near Visual Acuity
RA	Reading Acuity
RAR	Required Acuity Range
RNVA	Required Near Visual Acuity
ROV	Reciprocal of Vision
RR	Reading Rate
TgPS	Target Print Size
TPS	Threshold Print Size
VA	Visual Acuity
VAR	Visual Acuity Range
VIU	Visual Impaired User

CHAPTER ONE

INTRODUCTION

1.1. Background to Study

The Internet and associated technologies are integral parts of learning tool in the twenty first century. The e-learning environment is more and more indispensable because of the provisions and possibilities on the Internet. Generally, people who have vision disabilities find it difficult to obtain "appropriate" employment to match what their education prepared them for. This is against the backdrop that education is a vital factor in preparing students to develop into responsible adults who can take their place in the work force. It is, therefore, important that those with vision impairments are able to access as much as possible so that they can gain useful employment and participate constructively in society. For all students, vision is the primary sense necessary for successful learning and development (Kelly *et al*., 2000). One of the main difficulties caused by visual impairment is the problem of access to information, and with the advent of technology that is not adaptive to them, this difficulty is increasing (Armstrong *et al*., 2010). Without vision, students and teachers use speech to a much greater extent and a virtual classroom is needed to supplement the physical classroom and laboratory setting.

However users of e-learning systems with vision impairments will need to learn specific skills in order to take advantage of the learning tool. Such users have previously been disadvantaged due to inaccessible learning materials or instructional media which have not been adaptive to their specific need (Stoica *et al*., 2009). Problems faced by vision impaired users are different from those experienced by sighted users. Most e-learning environments are designed for sighted users, utilising complex visual images and interactive features; however users with acute vision impairments are not able to utilise these features and must rely on specialised applications to translate the contents of screen displays and documents into forms that are visible. Learning environments for people with physical disabilities need specific considerations in design and implementation to ensure their appropriateness and accessibility (Permvattana, 2013).

Universal Design (UD) approach is one of the most prominently discussed approaches to accessible e-learning. It entails designing instructional materials and learning activities (delivery methods, physical spaces, information resources, technology, personal interactions, assessments) so they are usable by all students without the need for adaption or specialised design (Burgstahler and Crawford, 2007). Burgstahler and Crawford also reiterated that applying universal design concepts in course planning ensured access to the content was maximised for most students and the need for particular adjustments was diminished though specific accommodations could be pursued for students with disabilities. Some e-learning models have been presented for students with disabilities. But, very few of these models are conceptual and holistic.

For application into an e-learning environment specifically for vision impaired students, most of the proposed accessibility models needed modification or honing in order to be effective. There have been very few holistic e-learning models that are related to accessibility and disabled students. Seale (2006) stated that there were very few original models, theories and metaphors published in the literature to illustrate or build best practice in accessible e-learning. Many of the approaches and models to e-learning for the disabled were based upon World Wide Web Consortium's (W3C) Web Content and Accessibility guidelines (WAI, 2004). Whilst the guidelines presented by the Web Accessibility Initiative provided a valuable source of checklists, an approach that relied upon lists of factors for compliance risks a disjointed end product that merely meet the requirements. In an effort to supplement the guidelines, several researchers have used these as a foundation for building further theories and/or tools.

Daniels and Elliott (2003) presented a set of generic guidelines and processes for testing the accessibility of e-learning Web sites, based upon an earlier version of the W3C Web Content Accessibility Guidelines in addition to the earlier work on usability and mobility by other researchers. The result was a generic set of guidelines. Whilst these guidelines were useful for ensuring e-learning Web sites are more accessible, the analysis focused on a detailed Web-document, does not present a holistic perspective and does not take into account other perspectives. Lazar *et al*. (2004) presented the Web Accessibility Integration Model on Web site accessibility, based upon the influences of stakeholder perceptions, societal foundations and Web accessibility. Lazar and colleagues reasoned that societal foundations were inadequate with regard to levels of accessibility as education curriculum as of the time does not include accessibility. The stakeholder perspectives included were those of the Web developer and client, who were the stakeholders who determined whether the Web site was built for accessibility. They suggested guidelines and tools that guide the Web developer and also provide a working definition for Web accessibility. Whilst stakeholder perspectives were essential in the development of all e-learning Websites, this model was not designed for direct application into the design of accessible e-learning environments for students with disabilities.

Web Accessibility Initiative (2007) presented an accessible e-learning model that was contextual in nature and centred on the aspect of stakeholder involvement. This model comprised accessibility drivers in the form of guidelines, standards and legal requirements, a wide collection of stakeholders in higher education who influenced or are influenced by accessibility, and the responses of these stakeholders via processes resulting in e-learning outcomes with some level of accessibility. This model provided a comprehensive approach to e-learning accessibility, and the focus on the stakeholders and their responses together with the drivers and mediators, enables a much richer understanding of the learning environment under study. Seale's contextualized model was a process model rather than a holistic design framework, with only partial applicability to accessibility for vision impaired students with specific requirements.

The most holistic model for accessibility and e-learning emanated from Kelly, Phipps and Swift (2005). This model is circular in format to illustrate that learning is a holistic activity and cultural, political and social aspects need to be considered. The model placed the learner's needs at the centre of the circle. Kelly and colleagues highlighted the need to consider issues of individual requirements, accessibility, usability of e-learning resources, the desired learning outcomes, and local factors including institutional and subject discipline aspects, as well as the technical infrastructure. These factors are placed within consideration of quality assurance where standards and guidelines provide a framework for development.

1.2. Statement of the Problem

Assistive technology (AT) provides means through which persons with visual impairment are empowered with adaptive devices, methods and other equipment for accessing multimedia information. Existing AT were designed as “one model fits all”, thereby limiting the usability of the assistive devices by vision impaired users, with varying degree requirements of sensitivity and specificity values.

There is that challenge in e-learning of exclusion of vision impaired users as a result of lack of adaptive usability and accessibility to e-learning platforms. Existing e-learning architectures failed to adjust to the calibration parameters of vision impaired users in their design considerations. The existing assistive devices were not designed to adaptively adjust its configurations to suit the requirements of vision impaired users. In order to mitigate this challenge, adaptive and intelligent-based multi-layered feed forward artificial neural network was developed with an adaptive calibrator capable of quantifying imprecise features of vision impaired users.

1.3. Aim and Objectives of the Study

The aim of this study is to develop a framework for a reusable intelligent access model to multimedia resources for vision impaired users in e-learning environment. In order to achieve this aim, the specific objectives are to:

i. develop adaptive calibration parameters for low acuity;
ii. develop a dynamically adaptive vision calibrator for vision impaired users;
iii. develop a dynamic thresholding algorithm for modeling visually impaired users;
iv. implement and evaluate dynamic thresholding algorithm;

1.4. Significance of the Study

This study is significant in providing intelligent access to vision impaired users. The study is envisaged to benefit both the learners and the instructors in e-learning platform. The vision impaired users would be able to learn adaptively at their own pace with reusable and reconfigurable learning contents. Most importantly, the intelligent-based model of the research work provides expert system functionality that keeps tracks of learners’ achievements and adaptively adjusts to learners’ needs.

1.5. Scope of the Study

The scope of this work is mainly on the vision impaired users of e-learning environment. The work does not address other forms of disabilities that might affect learning. The modified artificial neural network used supervised learning technique for developing dynamic thresholding model.

1.6. Limitation of the Study

The luminance calibration of assistive devices was not considered in the research work. This is because of the shift in concerns in luminance calibrations form users' perspective to technological innovation. The approach which was in the area of developing modified artificial neural network did not include unsupervised learning technique.

1.7. Glossary of Terms

Visual acuity	describes how well an individual sees details with his or her central vision; it is clarity of vision.
Print size	is height of the font with respect ascender and descender from the baseline.
Reading rate	is part of the broader umbrella of fluency and is measured in words read per minute
Sensitivity	is the proportion of instances classified positive and are positive of all the instances that are actually positive. It is also referred to True Positive Rate or Recall.
Specificity	is the proportion of instances classified negative and are negative of all the instances that are actually negative. It is also referred to as True Negative Rate.
False Positive Rate	is the proportion of negative instances incorrectly classified as positive.
False Negative Rate	is the proportion of positive instances incorrectly classified as negative.

Correct Rate	is the proportion of the correctly classified instances to the classified samples.
Error Rate	is the proportion of incorrectly classified instances to classified instances
Last Correct Rate	is the proportion of correctly classified instances to classified instance in the last classification performance update
Last Error Rate	is the proportion of incorrectly classified instances to classified samples in the last classification performance update
Inconclusive Rate	is the proportion of nonclassified instances to total number of instances
Classified Rate	is the proportion of classified instances to the total number of instances.
Visual Impairment	Is a decreased ability to see to a degree that causes problems
Degree of Visual Impairment	Is the visual field of sighted; the higher the visual field the better the sight

CHAPTER TWO

LITERATURE REVIEW

2.1. Concept of Related Terms

Several concepts were considered relevant in the course of this work. The list of the concepts included are not exhaustive neither does it reflect the limit of effort in this work. It is however a reflection of value attributed to these concepts of reference.

2.1.1. e-Learning

The origins of the term e-learning is not certain, although it is suggested that the term most likely originated during the 1980s, within the similar period frame of another delivery mode - online learning. While some authors explicitly defined e-learning, others implied a specific definition or view of e-learning in their article. These definitions materialize, some through conflicting views of other definitions, and some just by simply comparing defining characteristics with other existing terms. In particular, Gentleman, *et al*., (2004) disagrees with authors like Nichols and Hayasaka (2003) who defined e-learning as strictly being accessible using technological tools that are either web-based, web-distributed, or web-capable. There is a conceptual belief that e-learning not only covers content and instructional methods delivered via CD-ROM, Internet or an Intranet (Benson *et al*., 2002; Clark, 2002) but also includes audio- and videotape, satellite broadcast and interactive television is the one held by Ellis (2004).

Although technological characteristics are included in the definition of the term, Tavangarian *et al*. (2004) as well as Triacca, *et al*. (2004) felt that the technology being used was insufficient as a descriptor. Tavangarian *et al*. (2004) included the constructivist theoretical model as a framework for their definition by stating that e-learning is not only procedural but also shows some transformation of an individual's experience into the individual's knowledge through the knowledge construction process. Both Ellis (2004) and Triacca *et al*. (2004) believed that some level of interactivity needs to be included to make the definion truly applicable in describing the learning experience, even though Triacca *et al*. (2004) added that eLearning was a type of online learning.

As there is still the main struggle as to what technologies should be used so that the term can be referenced, some authors provide either no clear definition or a very vague reference to other terms such as online course/learning, web-based learning, web-based training, learning objects or distance learning, believing that the term can be used synonymously (Dringus and Cohen, 2005; Khan, 2001; Triacca *et al*., 2004; Wagner, 2001). What is abundantly obvious is that there is some uncertainty as to what exactly are the characteristics of the term, but what is clear is that all forms of e-learning, whether they be as applications, programs, objects, websites, etc., can eventually provide a learning opportunity for individuals.

Online learning can be difficult to define. Some prefer to distinguish the variance by describing online learning as "wholly" online learning (Oblinger and Oblinger, 2005), whereas others simply reference the technology medium or context with which it is used (Lowenthal *et al*., 2009). Others display direct relationships between previously described modes and online learning by stating that one uses the technology used in the other (Rekkedal *et al*., 2003; Volery and Lord, 2000). Online learning is described by most authors as access to learning experiences via the use of some technology (Benson, 2002; Carliner, 2004; Conrad, 2002). Both Benson (2002) and Conrad (2002) identify online learning as a more recent version of distance learning which improves access to educational opportunities for learners described as both non-traditional and disenfranchised. Other authors discuss not only the accessibility of online learning but also its connectivity, flexibility and ability to promote varied interactions (Ally, 2004; Hiltz and Turoff, 2005; Oblinger and Oblinger, 2005). Hiltz and Turoff (2005) in particular not only elude to online learnings' relationship with distance learning and traditional delivery systems but then, like Benson (2002) makes a clear statement that online learning is a newer version or, and improved version of distance learning. These authors, like many, believe that there is a relationship between distance education or learning and online learning but appear unsure in their own descriptive narratives.
The process of providing online courses on the Internet for users so that they can study and learn from any place and computing device (personal computer, mobile phone,

tablet, etc.) is referred to as e-learning. Even though e-learning has become an increasingly popular training option, it cannot rely just on the upload of contents to the Internet or the developments of new standards. However, it needs to offer a feasible, personalised way that facilitates and enhances the users' learning process by combining such contents appropriately (Garrido *et al*., 2016).

The increasing growth of technology based on internet has led to the emergence of numerous approaches devoted to the field of education reflected in the use of e-learning systems. The rate at which e-learning is being embraced is getting remarkably higher as many institutions have already installed web-based systems for offering online courses. These often complement traditional methods enabling users to engage from any place with their learning through various materials alongside or instead of face-to-face teaching delivery. The European Commission defines the e-learning process as the use of Internet and multimedia technologies to improve the quality of teaching through providing access to resources and educational services as well as enabling remote evaluation, exchange and collaboration between users and lecturers (Harrati *et al*., 2016).

Furthermore, e-learning introduces tremendous benefits to world organisations and stakeholders. Based on the previous literature and research, main advantages of e-learning that highly motivate users in efficiently learning contents include: access flexibility, on-demand availability, personalised instruction, timely content delivery, content standardisation, increased convenience, accountability, self-pacing, confidence, and interactivity. Further advantages of e-learning lie behind cost reduction, consistent delivery of learning materials, and enhancement of tracking for universities. Moreover, further research indicated that e-learning systems decrease costs of class-room equipment, training, printed materials, traveling, and labour (Zare *et al*., 2016).

2.1.2. e-Learning Environment Characteristics

The previous list of definitions illustrates several problems, two of which are (1) terms such as online, web-based, and e-learning are interchanged when describing the learning environment, and (2) some definitions and evaluation instruments discuss and use courses (Guilar and Loring, 2008) or programs (Clark, 2002) while others are based on learning objects (Nesbit *et al*., 2003; Tavangarian *et al*., 2004). Not only does the second issue lead to problems related to scope and the instructional characteristics that will be embedded based on the type of learning environment, it also highlights the terms used to define an instance of such learning environments. To illustrate, a course can and has been seen as a "program" of instruction, whereas a program is referred to a pluralized version of many courses (Clark, 2002; Guilar and Loring, 2008). Though used interchangeably by some, there are many courses in a program but never the reverse; many programs in a course.

The learning environment can be identified as a Learning Management System (LMS), a Course Management System (CMS), a Virtual Learning Environment (VLE) or even a Knowledge Management System (KMS) (Khan, 2001; Nichols, 2003; Spector, 2007; Wilen-Daugenti, 2009). As much as the terms are used synonymously, some see each term differently. Gagné *et al.* (2005) define a CMS as having tools associated with the development and delivery of courses which are placed onto the Internet, further defined as a Collaborative Learning Environment, but the authors define an LMS as more of management system for the delivery of online learning.

Nichols (2003) agrees that the LMS is mainly used for online courses and components, yet reverts to the use of the term eLearning to identify the tools used to deliver the learning experience. Wagner (2001) and WilenDaugenti (2009) referred to some of the terms synonymously. WilenDaugenti (2009) interchanged the terms CMS, LMS and VLE, whereas Wagner (2001) used LMS, KMS and Knowledge Content Distributors (KCD), a term stated as the predecessor of all, as the same. Additional learning environment terms are either referring to tools that can be used within the environment or the type of learning that will be delivered within the system. Learning objects is a term that represents the management of the environment. There is some agreement that learning objects are digital resources that can be reused to assist with learning (Nichols, 2003; Spector, 2007). Although learning object is used synonymously with content object, knowledge object, and reusable information object, it is, in this form, the most commonly used term for this definition (Wagner, 2001).

Another core characteristic of learning environments are the design methodology. Courses, programs, and learning objects, which are available in OLEs, can either be self-paced, self-directed or instructor-led. The most common form of distance-related course design in traditional educational environments, like universities, is instructor-led described as an environment where an instructor guides learners through the required instruction content. In this type of learning environment, the instructor controls the instructional sequencing and pacing and all learners participate in the same learning activities at specified times (Rhode, 2009).

This learning environment is different from learning that occurs in a self-paced environment. Self-paced is a descriptor used for learning environments that enable individuals to study online in their own time and at their own pace, from their own location. This mode of learning provides the learner more autonomy to proceed at their own pace, while their progress is monitored to assess their achievement (Rhode, 2009; Spector *et al*., 2008). When the term self-directed is used, it is often in reference to all types of distance learning. It is defined by Garrison (2003) as a mode of learning which is learner-controlled; where the learner is more in charge of their own learning and they monitor and manage the cognitive and contextual aspects of their learning. Self-directed can also be perceived as independent learning, which has no learner to learner interactions.

2.1.3. Types of e-learning

There are diverse ways of classifying e-learning. According to Algahtani (2011), there have been some classifications based on the extent of their engagement in education. Some classifications are also based on the timing of interaction. Algahtani (2011) divided e-learning into two basic types, consisting of computer-based and internet-based e-learning. According to Algahtani (2011), the computer-based learning comprises the use of a full range of hardware and software generally that are available for the use of Information and Communication Technology and also each component can be used in either of two ways: computer managed instruction and computer-assisted-learning. In computer assisted-learning, computers are used instead of the traditional methods by providing interactive software as a support tool within the class or as a tool for self-learning outside the class. In the computer-managed instruction, however, computers are employed for the purpose of storing and retrieving information to aid in the management of education.

The Internet-based learning according to Almosa (2001) is a further improvement of the computer-based learning, and it makes the content available on the internet, with the readiness of links to related knowledge sources, for examples e-mail services and references which could be used by learners at any time and place as well as the availability or absence of teachers or instructors (Almosa, 2001). Algahtani (2011) described the completely online mode as “synchronous” or “asynchronous” by the application of optional timing of interaction. The synchronous timing comprises alternate online access between teachers or instructors and learners, or between leaners, and the asynchronous allows all participants to post communications to any other participant over the internet (Algahtani, 2011; Almosa and Almubarak, 2005).

The synchronous type allows learners to discuss with the instructors and also among themselves via the internet at the same time with the use of tools such as the videoconference and chat rooms. This type according to Almosa and Almubarak (2005) offers the advantage of instantaneous feedback. The asynchronous mode also allows learners to discuss with the instructors or teachers as well as among themselves over the Internet at different times. It is, therefore, not interaction at the same moment but different times, with the use of tools such as thread discussion and emails (Almosa and Almubarak, 2005; Algahtani, 2011), with an advantage that learners are able to learn at a time that suits them whilst a disadvantage is that the learners will not be able to receive instant feedback from instructors as well as their colleague learners (Almosa and Almubarak, 2005).

2.1.4. e-Learning Environment and Adaptability

In recent years, there was heightened awareness of the potential benefits of adaptivity in e-learning. This has been mainly driven by the realization that the ideal of individualised learning (that is, learning tailored to the specific requirements and preferences of the individual) cannot be achieved, especially at a “massive” scale, using traditional approaches. Factors that further contribute in this direction include: the diversity in the “target” population participating in learning activities (intensified by the gradual attainment of life-long learning practices); the diversity in the access media and modalities that one can effectively utilise today in order to access, manipulate, or collaborate on, educational content or learning activities, alongside with a diversity in the context of use of such technologies; the anticipated proliferation of free educational content, which will need to be "harvested" in order to "assemble" learning objects, spaces and activities; etc. There exist currently several systems which employ adaptive techniques to enable or facilitate different aspects of learning (Brusilovsky, 1999). Adaptive behaviour on the part of a learning environment can have numerous manifestations. Instead of attempting to exhaustively enumerate all of these, a high-level categorization will be provided, which suffices for the analysis in the following section. The broad and partially overlapping categories that are being referred to are: adaptive interaction, adaptive course delivery, content discovery and assembly, and, finally, adaptive collaboration support.

2.1.5. Types of Adaptations in e-learning

In e-learning, there are four types of adaptations. The adaptations are: (i) adaptive interaction, (ii) adaptive course delivery, (iii) content discovery and assembly and (iv) adaptive collaboration support.

i. *Adaptive Interaction* refers to adaptations that take place at the system's interface and are intended to facilitate or support the user's interaction with the system, without, however, modifying in any way the learning "content" itself. Examples of adaptations at this level include: the employment of alternative graphical or colour schemes, font sizes, etc., to accommodate user preferences, requirements or (dis-) abilities at the lexical (or physical) level of interaction; the reorganisation or restructuring of interactive tasks at the syntactic level of interaction; or the adoption of alternative interaction metaphors at the semantic level of interaction. Although interface adaptations can be thought of as generally independent from the material or "content" delivered through a learning environment, this is not usually the case with learning *activities*. The major differentiating factor being the emphasis on ensuring and optimising "content" attainment in the former case, versus the emphasis on supporting a process in the case of activities. The dependency of learning activities on interface adaptations is a natural consequence of the fact that the interface encapsulates the very "tools" for carrying out an activity, be it interpersonal communication, collaboration towards problem-solving.

ii. *Adaptive Course Delivery* constitutes the most common and widely used collection of adaptation techniques applied in learning environments today. In particular, the term is used to refer to adaptations that are intended to tailor a course (or, in some cases, a series of courses) to the individual learner. The intention is to optimise the "fit" between course contents and user characteristics/requirements, so that the "optimal" learning result is obtained, while, in concert, the time and interactions expended on a course are brought to a "minimum". In addition to time and effort economy, major factors behind the adoption of adaptive techniques in this context include: compensating for the lack of a human tutor (who is capable of assessing learner capacity, goals, etc., and advising on individualised "curricula"), improving subjective evaluation of courses by learners, etc. The most typical examples of adaptations in this category are: dynamic course (re-structuring); adaptive navigation support; and, adaptive selection of alternative (fragments of) course material (Brusilovsky, 2001).

iii. *Content Discovery and Assembly* refers to the application of adaptive techniques in the discovery and assembly of learning material/"content" from potentially distributed sources/repositories. The adaptive component of this process lies with the utilisation of adaptation-oriented models and knowledge about users typically derived from monitoring, both of which are not available to non-adaptive systems that engage in the same process. There is an explicit distinction between the perspective of the individual learner wishing to locate relevant material within a (possibly constrained) corpus, and the perspective of the author or "aggregator" who undertakes the task of putting together a course from existing materials and targeting a specific audience or, seen differently, collecting and tailoring material for accommodating specific user/context characteristics.

iv. *Adaptive Collaboration Support* is intended to capture adaptive support in learning processes that involve communication between multiple persons (and, therefore, social interaction), and, potentially, collaboration towards common objectives. This is an important dimension away from "isolationist" approaches to learning, which are at odds with what modern learning theory which increasingly emphasizes: the importance of collaboration, cooperative learning, communities of learners, social negotiation, and apprenticeship in learning (Wiley, 2003). Adaptive techniques can be used in this direction to facilitate the communication/collaboration process, ensure a good match between collaborators, etc.

2.2. Vision Impaired Users of e-learning Platforms

The level of vision-ability of users of e-learning platform has a great impact on the reading rate. It also determines the level of screen magnification suitable for such users. Several low vision aids (LVA) are available to help in enhancing visibility of print text (Mansfield *et al*., 1996). Another factor influencing level of vision-ability is visual acuity. Visual acuity (VA) is the measurement of the ability to see details.

In order to mitigate the challenge of vision impairment in a print text, the font size of the print text can be increased. The process of increasing the print text size to boost vision is referred to as magnification (Cheong *et al*., 2002). Moreover, screen reading assistive devices are used to reduce the limitation of low vision. Some of the software deployed in this regards are Jaws, Microsoft NVDA, GNopernicus, Window-eye, Supernova, e.t.c. (Mahajan and Nagendra, 2014).

2.3. Reading Rates and Print Sizes

Reading rate is part of the broader umbrella of fluency and is measured in words read per minute, while fluency is a bit more subjective. Rate is a key factor in fluency as a whole. For example, reading rate for each sentence on the Bailey-Lovie text chart was plotted against print size. A smooth curve was fitted to the data and Critical Print Size (CPS) was selected by eye (at N12 [1.6 M]), that 12 font point number or size (N) and 1.6 magnification ratio (M). Text VA was the smallest print size the subject could read (N6 [0.8 M]) (Cheong *et al*., 2002; Lueck *et al*., 2003; Tuan *et al*., 2000).

Maximum reading rate (MRR) was taken as the mean of the reading rates for print sizes at and above CPS. For example, from Figure 2.1, MRR is the mean of reading rates at N12 and all print sizes larger. MRR and CPS without LVA were determined three times with different Bailey-Lovie text charts. The mean of the three measures of MRR was used for analyses, while mean CPS was selected to the nearest whole line.

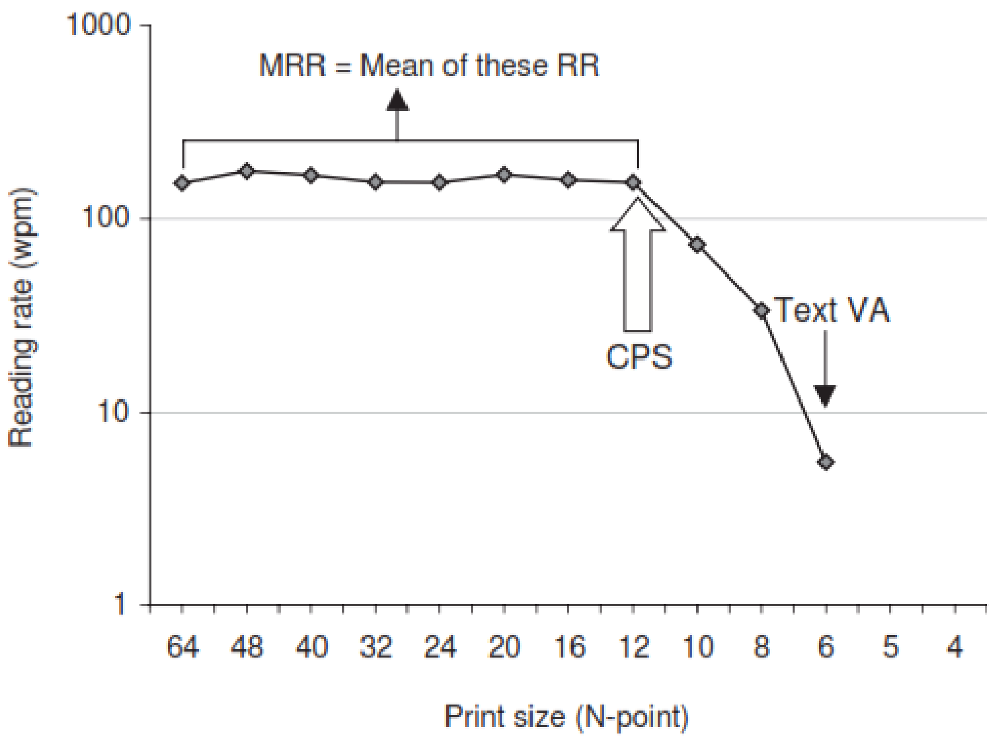

Figure 2.1. Reading rate versus print size (Source: Lovie-Kitchin, Bevan, & Hein, 2001)

In Figure 2.1, MRR was computed as the mean of the reading rates for print sizes at and above CPS. However, reading rate with LVA in some cases was reduced despite large print sizes. This is because few characters were visible in the field of view as in Figure 2.2. Therefore, when reading rates on large print sizes were less than 90 percent of the reading rate at CPS, they were excluded from the calculation. For example, in Figure 2.2, MRR was the mean of reading rates at print sizes from N20 (2.5 M) to N8 (1.0 M).

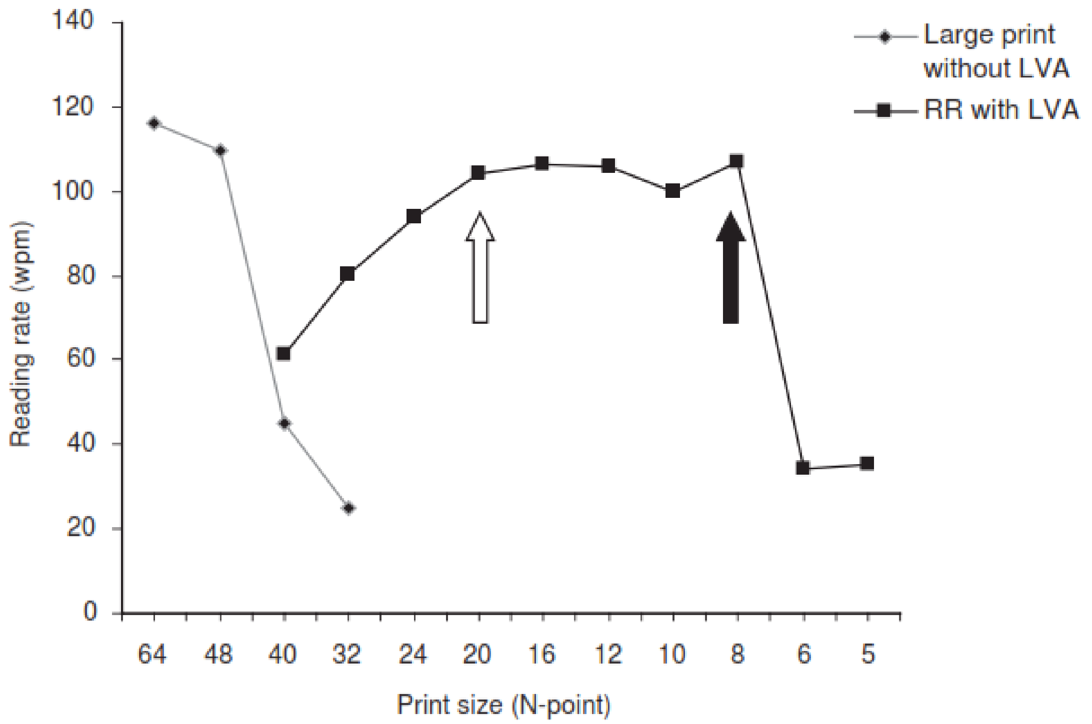

Figure 2.2. Reading rate versus print size with and without LVA (Source: Flom *et al*., 1993)

2.4. Screen Magnification

One of the corrective measures to vision impaired users is screen magnification. It is the act of increasing the size of the print text. Although there are improvements in the assessment of visual functions, appropriate determination of magnification for reading still often requires a trial and error approach. Research work has shown that with accurate and systematic assessments of vision, the required magnification can be predicted but this magnification needs to be much higher than has been previously recommended (Lovie-Kitchin and Whittaker, 1999).

Low vision is defined as permanent vision loss that is not correctable with spectacles, contact lenses or surgical intervention and that interferes with normal daily life. Reading is one of the most highly-valued activities in human society. Any ocular disorder that deprives people of the ability to read causes severe restriction of daily activities. This disability may be improved by various low vision aids (LVA) such as hand-held, stand and spectacle-mounted magnifiers, telescopes or electronic reading aids. To provide the appropriate LVA to assist people with vision impairment to retain their reading ability, accurate and efficient calculation of the required magnification is necessary as part of vision impairment rehabilitation (Cheong *et al*., 2002).

In determining magnification for vision impaired users, Lebenson used method of reciprocal vision to find Best corrected Distance Acuity (BDA) and Near Target Acuity (NTA) (Cheong *et al.*, 2002). Magnification (M) was then computed as the ratio of denominator of distance snellen fraction to denominator of near snellen fraction of target acuity. In order to enhance computation of magnification, Kestenbaum's method was introduced. This method made the following assumptions: (i) DVA and NVA can be equated, (ii) the reference addition is +2.50D, (iii) the Desired Acuity Level (DAL) is 6/15 Snellen equivalent (0.4 logMAR) at near. Kestenbaum's formular for computing magnification is the reciprocal of DVA divided by four (Kestenbaum & Sturman, 1956). However, application of this method could not fully mitigate the challenges of poor prediction of Near Acuity.

Light-house considers NVA instead of DVA so as to overcome the inherent limitations in the two previous approaches (Cheong *et al.*, 2002). This method assumes DAL to be 1M(6/15 Snellen equivalent at 40cm) or 8 point print (N8) with a reference addition of

+2.50 D. The formula used for the computation of magnification is 2.5 x NVA(M unit) divided by four.

After review was carried out by Cole (1993), limitation of under-estimation of magnification ratio in all the previous techniques was discovered when compared with final prescription. Over simplicity of computations were some of the reasons for limitations found in the existing methods. The equations only consider VA and ignore the Desired Reading Material (DRM) or make assumption of 1M (N8) print size always.

To improve accuracy, Cole introduced another equation which is called 'Reciprocal of Vision'. With this method, magnification is predicted based on the DVA and the Required NVA (RNVA). The RNVA can be predicted from the Target Reading Materials. It assumes DVA is equivalent to NVA and reference distance is 40 cm. Cole's formula for computing magnification is 2.5 x DVA divided by four x Required NVA (Cole, 1993). The introduction of the formula did not still remove the problem of under-estimation when compared with the final magnification prescribed as a result of some factors affecting reading with magnification (Cole, 1993; Flom *et al*., 1993). These factors are restricted field of view, reduced illumination, aberrations and difficulty in manually adjusting magnifiers (Ortiz *et al*., 1999).

In order to mitigate these factors, Lovie-Kitchin and Whittaker introduced Acuity Reserve. Acuity Reserve is the ratio of Print Size that the learner intends to read to Threshold Print Size (TPS). TPS is the Text Visual Acuity (TVS) which is the smallest print size that could be read but does not give Maximum Reading Rate (MRR). Several research work demonstrated that the Reading Rates of normally sighted and vision impaired users increase as Print Size increases from threshold (Cheong *et al*., 2002; Lovie-Kitchin *et al*., 2001; Lueck *et al*., 2003). Fluent Reading is not possible if the Print Size is at or close to Threshold irrespective of the level of vision (Berget *et al*., 2016; Lowe and Drasdo, 1990).

The work was, however, limited by the use of fixed or static Acuity Range which was generalised from data received from groups of users with vision impairment. Some of the users might need more Acuity Range while some might need less for fluent reading. This implies that Fixed Acuity Range may over or under-estimate Acuity

Range for individuals. Consequently, the work of Legge and Colleagues suggested individual-based Acuity Range instead of static Acuity Range (Foley, 2008; Legge *et al*., 1992; Mansfield *et al*., 1996; Ortiz *et al*., 1999).

In dynamic Acuity Reserve computation, measurement of Reading Rates at different Print Sizes is used to compute an Individual's Required Acuity Reserve for Maximum Reading Rate. It is calculated as the ratio of Critical Print Size to Threshold Print Size. The limitation of this individualised approach has to do with increased complications and complexities since it requires measurement of learners' Reading Rates at a number of different Print Sizes.

All these approaches computed Magnification without Low Vision Aids (LVA). With the use of LVA, viewing distance is of paramount importance in the computation of magnification. Magnification is calculated in terms of Equivalent Viewing Distance (EVD) (Dickinson and Fotinakis, 2000; Tuan *et al*., 2000).

2.5. Related Empirical Work on e-learning Environment

e-learning environment is an electronic-based avenue for knowledge transfer and acquisitions in terms of domain of learning. Several contributions from different authors in e-learning environment are summarised in Table 2.1

Table 2.1. Summary of Existing e-learning Environment

Author/Year	Problem being solved	Technique/method	Achievement	Scope/Limitation
(Akkoyunlu, 2016)	Usage problem	Continuance usage intention and integrated models	Continuance usage model	Based on cognitive, technology and information system continuance model
(Alotaibi, 2016)	Relationship between Self-Directed Learning Readiness (SDLR) and Users' Perception of Learning Environment (SPLE)	Descriptive design	SPLE determines the level of SDLR; the level of SDLR positively influence student's academic performance	Limited to nursing users
(Barak and Levenberg, 2016)	Thinking flexibility challenges in users	A six-stage study was used	Flexibility Thinking in Learning (FTL) scale	Acceptance of new or changing technologies, open-mindedness to others' ideas and adapting to changes in learning situations
(Christ and Thews, 2016)	Numerical complexity of simulation models in e-learning	Server-client browser based simulation	Simulation of complex biological processes and use in e-learning environment	Biomedical applications
(Fatahi and Moradi, 2016)	Poor quality of system interaction based on behaviour factors	Computational model for user's desirability based on personality in e-learning	High accuracy relationship between personality and emotions	Behaviour factors: personality, mood and emotion
(Garc, Ad, and Antonia, 2016)	Tutor-centred e-learning challenges	Six-element based self-learning methodology	Improved skill acquisition and patient safety	Clinical training

2.6. Artificial Neural Network and Modelling

Many tasks involving intelligence or pattern recognition are extremely difficult to automate, but appear to be performed very easily by humans. For instance, humans recognise various objects and make sense out of the large amount of visual information in their surroundings, apparently requiring very little effort. It stands to reason that computing systems that attempt similar tasks will profit enormously from understanding how humans perform these tasks, and simulating these processes to the extent allowed by physical limitations. This necessitates the study and simulation of Neural Networks. The neural network of an human is part of its nervous system, containing a large number of interconnected neurons (nerve cells). "Neural" is an adjective for neuron, and "Network" denotes a graph like structure. Artificial Neural Network (ANN) refers to computing systems whose central theme is borrowed from the analogy of biological neural networks. Artificial Neural Networks are also referred to as "Neural Nets", "parallel distributed processing systems" and "connectionist systems". For a computing system to be called by these pretty names, it is necessary for the system to have a labeled directed graph structure where nodes perform some simple computations. From elementary graph theory, it is recalled that a "Directed Graph" which consists of a set of "Nodes" (vertices) and a set of "Connections" (edges/links/arcs) connecting pairs of nodes. In a neural network, each node performs some simple computations, and each connection conveys a signal from one node to another, labeled by a number called the "Connection Strength" or "Weight" indicating the extent to which a signal is amplified or diminished by connection. This system is the alternative for human expertise and knowledge. Artificial Neural Networks are modeled closely following the brain and therefore a great deal of terminology is borrowed from neuroscience.

Kurban investigated that an artificial neural network are non-linear mapping systems with a structure loosely based on principles observed in the biological nervous systems. In greatly simplified terms, a typical real neuron has a branching dentritic tree that collects signals from many other neurons in a limited area; a cell body that integrates collected signals and generates a response signal (as well as manages metabolic functions); and along branching axon that distributes the response through contacts with dentritic trees of many other neurons. The response of each neuron is a relatively simple non-linear function of its inputs and is largely determined by the strengths of the connections from its inputs. In spite of the relative simplicity of the individual units, systems containing many neurons can generate complex and intersecting behaviours (Kurban, 2004).

In general terms, a NN consists of large number of simple processors linked by weighted connections. By analogy, the processing nodes may be called "neurons". Each node output depends only on the information that is locally available at the node, either stored internally or arriving via the weighted connections. Each unit receives inputs from many other nodes and transmits its output to other nodes. By itself, a single processing element is not very powerful; it generates a scalar output with a single numerical value, which is a simple non-linear function of its inputs. The power of the system emerges from the combination of many units in an appropriate way. A network is utilised different function by varying the connection topology and the values of the connecting weights. Complex functions can be implemented by connecting the units together with appropriate weights. It has been shown that a sufficiently large network with an appropriate structure and property chosen weights can approximate with arbitrary accuracy any function satisfying certain broad constraints (Dongare, Kharde and Kachare, 2012). This model is a drastically simplified approximation of real nervous systems. The intent is to capture the major characteristics important in the information processing functions of real networks without varying too much about the physical constraints imposed by biology. Artificial NN are made up of simple, highly interconnected processing units called neurons, each of which performs two functions, namely, aggregation of its inputs from other neurons or the external environment and generation of an output from the aggregated inputs. Through this simple structure, neural networks have been shown to be able to approximate most continuous functions to any degree of accuracy, by choice of an appropriate number of neuron units (Bota & Swanson, 2007).

2.6.1. Feed Forward Networks

This is a subclass of acrylic networks in which a connection is allowed from a node in layer i only to nodes in layer i+1. These networks are succinctly described by a sequence of numbers indicating the number of nodes in each layer. For instance, a 3-2-

3-2 network is a feed forward network; it contains three nodes in the input layer (layer 0), two nodes in the first hidden layer (layer 1), three nodes in the second hidden layer (layer 2), and two nodes in the output layer (layer 3). These networks, generally with no more than four such layers, are among the most common neural nets in use, so much so that some users identify the phrase "neural networks" to mean only feed forward networks.

Conceptually, nodes in successively higher layers abstract successively higher level features from preceding layers. In the literature on neural networks, the term "feed forward" has been used sometimes to refer to layered or acrylic networks (Villaverde *et al*., 2006).

2.6.2. Neural Learning

It is reasonable to conjecture that neurons in an animal's brain are "hard wired." It is equally obvious that animals, especially the higher order animals, learn as they grow. How does this learning occur? What are possible mathematical models of learning? In this section, some of the basic theories of biological learning and their adaptations for artificial neural networks were summarized. In artificial neural networks, learning refers to the method of modifying the weights of connections between the nodes of a specified network. Learning is the process by which the random-valued parameters (Weights and bias) of a neural network are adapted through a continuous process of simulation by the environment in which network is embedded. Learning rate is defined as the rate at which network gets adapted. Type of learning is determined by the manner in which parameter change takes place. Learning may be categorized as supervised learning, unsupervised learning and reinforced learning. In Supervised learning, a teacher is available to indicate whether a system is performing correctly, or to indicate a desired response, or to validate the acceptability of a system's responses, or to indicate the amount of error in system performance. This is in contrast with unsupervised learning, where no teacher is available and learning must rely on guidance obtained heuristically by the system examining different sample data or the environment. Learning is similar to training, that, one has to learn something which is analogous to one has to be trained. A neural network has to be configured such that the application of a set of inputs produces (either 'direct' or via a relaxation process) the desired set of outputs. Various methods to set the strengths of the connections exist.

One way is to set the weights explicitly, using a priori knowledge. Another way is to 'train' the neural network by feeding it teaching patterns and letting it change its weights according to some learning rule. The learning situations can be categorised in two distinct sorts. These are:

2.6.2.1. Supervised Learning

Supervised learning or Associative learning involves training of the network by providing it with input and matching output patterns. These input-output pairs can be provided by an external teacher, or by the system which contains the neural network (self-supervised). Example: An archaeologist discovers a human skeleton and has to determine whether it belonged to man or woman. In doing this, the archaeologist is guided by many past examples of male and female skeletons. Examination of these past examples (called the training set) allows the archaeologist to learn about the distinctions between male and female skeletons. This learning process is an example of supervised learning, and the result of learning process can be applied to determine whether the newly discovered skeleton belongs to man or woman.

2.6.2.2. Unsupervised Learning

Unsupervised learning or Self-organisation involves training of an output unit to respond to clusters of pattern within the input. In this paradigm, the system is supposed to discover statistically salient features of the input population. Unlike the supervised learning paradigm, there is no a priori set of categories into which the patterns are to be classified; rather the system must develop its own representation of the input stimuli. Example: In a different situation, the archaeologist has to determine whether a set of skeleton fragments belong to the same dinosaur species or need to be differentiated into different species. For this task, no previous data may be available to clearly identify the species for each skeleton fragment. The archaeologist has to determine whether the skeletons (that can be reconstructed from the fragments) are sufficiently similar to belong to the same species, or if the differences between these skeletons are large enough to warrant grouping them into different species. This is an unsupervised learning process, which involves estimating the magnitudes of differences between the skeletons. One archaeologist may believe the skeletons belong to different species, while another may disagree, and there is no absolute criterion to determine who is correct.

2.6.2.3. Reinforced Learning

Reinforcement Learning is type of learning considered as an intermediate form of the above two types of learning. Here the learning machine does some action on the environment and gets a feedback response from the environment. The learning system grades its action good (rewarding) or bad (punishable) based on the environmental response and accordingly adjusts its parameters. Generally, parameter adjustment is continued until an equilibrium state occurs, following which there will be no more changes in its parameters. The self organising neural learning may be categorised under this type of learning (Huang and Huang, 2013).

2.6.3. Back Propagation Network

The back propagation algorithm is used in layered feed-forward ANNs (Herrero *et al.*, 2009). This means that the artificial neurons are organized in layers, and send their signals "forward", and then the errors are propagated backwards. The network receives inputs by neurons in the *input layer*, and the output of the network is given by the neurons on an *output layer*. There may be one or more intermediate *hidden layers*. The back propagation algorithm uses supervised learning, which means that the algorithm is provided with examples of the inputs and outputs the network is to compute, and then the error (difference between actual and expected results) is calculated. The idea of the back propagation algorithm is to reduce this error, until the ANN *learns* the training data.

The training begins with random weights, and the goal is to adjust them so that the error will be minimal. Back propagation network has gained importance due to the shortcomings of other available networks. The network is a multi layer network (multi layer perception) that contains at least one hidden layer in addition to input and output layers. Number of hidden layers and numbers of neurons in each hidden layer is to be fixed based on application, the complexity of the problem and the number of inputs and outputs. Use of non-linear log-sigmoid transfer function enables the network to simulate non-linearity in practical systems (Csábrági *et al.*, 2017).

Implementation of back propagation model consists of two phases. First phase is known as training while the second phase is called Testing. Training, in back propagation is based on gradient decent rule that tends to adjust weights and reduce system error in the network. Input layer has neurons equal in number to that of the inputs. Similarly, output layer neurons are same in the number as number of outputs. Number of hidden layer neurons is deciding by trial and error method using the experimental data (Park, 2013).

2.6.4. ANN Development and Implementation

In the work of Xia *et al*. (2015), both ANN implementation and training were developed, using the neural network toolbox of MATLab. Different ANNs were built rather than using one large ANN including all the output variables. This strategy allowed for better adjustment of the ANN for each specific problem, including the optimisation of the architecture for each output.

2.6.5. ANN Training and Prediction quality

One of the most relevant aspects of a neural network is its ability to generalise, that is, to predict cases that are not included in the training set. One of the problems that occur during neural network training is called over fitting. The error on the training set is driven to a very small value, but when new data is presented to the network, the error is large. The network has memorised the training examples, but it has not learned to generalise to new situations. One method for improving network generalization is to use a network that is just large enough to provide an adequate fit (Dongare *et al.*, 2012).

The larger network used the more complex functions the network can create. There are two other methods for improving generalisation that are implemented in MATLab Neural Network Toolbox software: regularisation and early stopping. The typical performance function used for training feed forward neural networks is the mean sum of squares of the network errors,

It is possible to improve generalisation, the performance function can be modified by adding a term that consists of the mean of the sum of the squares of the network weights and biases. Using this performance function causes the network to have smaller weights, biases, smother network response and less likely to over fit. Once the different stages of the training process and the ANN structure had been determined, and before the optimisation procedure is developed, it is important to estimate the ANN prediction qualities. There is excellent agreement of predicted values and expected values. This close agreement shows that the ANN can be used in the data analysis, of theoretical work to generate the missing data in the theoretical program. The results of model ANN are compared with the hydrodynamic simulation data (Park, 2013).

2.7. e-Learning Modelling and Artificial Neural Network

e-learning is an emerging technology in the field of innovative teaching and learning. It provides a virtual classroom with all the facilities of conventional and advanced methods of teaching. The success rate of implementation of e-learning technology can be vastly improved by the use of neural networks. Using neural networks the registered students can be classified on various factors viz. learning abilities, goal of study etc. and hence be provided suitable integrated environments for study. Neural networks can further be used for evaluation purpose.

e-Learning uses modern educational technologies to implement an ideal learning environment through integrating the information technology into curriculum, which can embody the learning styles of students' main-body function, reform the traditional teaching structure and the essence of education thoroughly. Although the current e-learning systems have many merits, many of them only treat advanced information technology as simple communication tools, and release some learning contents and exercises in the network.

The successful implementation of e-learning systems depend a great deal on whether these systems can provide an adaptive system with an adaptive interface to the learners depending upon various factors like their learning abilities, professional background, learning goals etc. To provide these features, it is necessary that the e-learning systems should be able to classify the learners. Neural networks can be effectively used for classification.

A model by Kelly, Nevile *et al*. (2008) placed a variety of student needs into an outer circle, including disabilities, cultural, economic, geographical and social needs. The inner circle contained collection of learning activities and resources that related to the learning objectives. This holistic model for Web accessibility for e-learning focused on accessible learning outcomes rather than accessible resources. Whilst all these models provided valuable input in the design of specialised e-learning environments for the vision impaired, there is much subjective interpretation when such models are applied in practice. It is difficult in many circumstances to define what is included in an object or process and how these interact with each other, as well as how these contribute to achieving the overall goals and objectives.

Rosis *et al*. (2003) implemented a 3D embodied intelligent agent, called GRETA, which can be animated in real-time. GRETA was made of three components. These related components are: a face expression component, an agent mind, and a communication component. The agent mind component consisted of personality and emotions components. These components simulated how emotions are triggered and decayed over time based on the agent's personality. Two variables were used to calculate the intensity of emotions: uncertainty and utility. Uncertainty is the agent's beliefs about the world and utility assigned to the achievement of goals. A belief network for triggering the emotion was designed. Five Factor Model (FFM) and the Ortony, Clore and Collins (OCC) model were used to model personality and emotions, respectively. Unfortunately, there is no report of the performance of the implemented system and it should be mentioned that user's desirability based on personality and mood was not considered in the model. Moreover, the goal of the research work was to make the agents more believable and there was no attempt to predict the user's emotion.

Egges *et al*. (2004) implemented a generic model of personality, mood, and emotions in a conversational virtual human. The model could linearly update the current mood and emotions based on personality and the history of mood and emotions. To update a current emotional state, personality, history of current emotional state, and decay of the emotional state were considered. The proposed framework was evaluated in a small interaction system which simulated agent's behaviour. It was shown how the framework can be integrated with an application such as an expressive MPEG-4 talking head with speech synthesis. In this research, the OCC model and FFM were used to model emotion and personality receptively. In this model, the relationship between the user's goals and personality in determining emotions were not considered. However, predicting the user's emotion based on environmental events was not considered.

Gratch and Marsella (2004) proposed a general computational framework of emotion for human-like autonomous agents. Unlike the other research, Gratch and Marsella (2004) tried to focus more details on OCC variables which are important in calculating emotion such as desirability, likelihood, casual attribution and coping. Based on the framework, a model was proposed which was domain-independent and used in a significant social training application. Several rules were used to calculate intensity of emotions using appraisal variables. It should be mentioned that this model did not consider effects of personality to calculate appraisal variables such as desirability.

Moshkina (2006) presented an integrative behaviour framework for an affective agent called Traits, Attitudes, Moods, and Emotions (TAME). TAME was evaluated into a human-robot application. The input of the framework was relevant perceptual information, such as the categories of visible objects and distances to them. Based on the perceptual information, affective module which combined personality traits, attitudes, mood, and emotions selects a suitable behaviour and presents it to a user. The results showed that affective behaviour provided many benefits such as ease of use and pleasantness of interaction. It should be noted that the main goal of the research was to make a human-robot more believable. The affective module made an attempt to report affective state of agent to generate suitable behaviour. It was not attempting to predict users' emotion. Moreover, users' goals and relationship between them and user's personality were not considered to calculate users' emotions.

Dang and Duhaut (2009) proposed a generic model of emotion called Generic Robotic Architecture to Create Emotions (GRACE). GRACE combined the OCC model and Lazarus-Scherer theory (Smith and Lazarus, 1990) for its emotion component, and used Myers-Briggs Type Indicator (MBTI) for its personality component. GRACE considered the intensity of emotions based on personality types. The proposed model was validated through asking a group of people to evaluate the personality of the robot.

The results show that the people could detect different personality and emotions in GRACE. The most important difference between GRACE and previous models is using a combination model of emotion rather than using one model but such as previous studies users' goals and relationship between them and user's personality was not considered to calculate users' desirability.

Santos *et al*. (2011) used artificial intelligence agents who have personality, mood, and emotions similar to humans in a group decision-support system. The main goal of this research was to improve the negotiation process through argumentation using the affective characteristics of the involved participants. FFM, Pleasure, Arousal, and Dominance (PAD), and the OCC model were used to simulate agents who act similar to humans. In this research as same as previous, user's desirability based on personality, user's goals and environmental events were not calculated. Kazemifard *et al*. (2011) presented a new computational emotional model based on OCC model that maps the environmental events and agents' actions into emotional states. The model applied in decision-making by agents, so that agents can behave similar to humans. The main characteristics of the model is adaptable to different domains and can be implemented as an individual module in software agents but it is based on emotion and it does not consider personality effects on emotion.

All the previous studies were focused to make virtual agents more plausible by trying to simulate human type affects. Subsequent studies propose models to incorporate personality, mood, and emotion in e-learning environments. Fatahi and Ghasem-Aghaee (2010) designed a Virtual Tutor Agent (VTA) and Virtual Classmate Agent (VCA) who have personality and emotion. VTA used a teaching style appropriate for a learner based on the learner's learning style. Also, VTA proposed a suitable VCA for the learner based on a situation at hand. The VCA selected tactics to interact with the learner and was able to cooperate intelligently with the learner. The results indicate that the presence of VCA leads to improvement in the learning process and attractiveness of their virtual learning environment. In this research an expert system was used, and VTA and VCA used a set of fixed given rules to interact with users. Users' disability based on relationship between personality and user's goals was not calculated. Conati and Zhou (2002) implemented a probabilistic model that assesses student emotional reaction during interaction with an educational game. Conati and

Zhou used a dynamic decision network to model the decision of a pedagogical agent. Personality traits of FFM model was considered to describe a student's personality traits and OCC model to describe the student's emotional state. It should be mentioned that Conati and Zhou (2002) did not try to calculate and predict desirability. The model was used to generate behaviours for their pedagogical agents. Several studies have been carried out in order to consider human characteristics in computer science with emphasize in e-learning environments. In all the existing research work and models proposed, there has been no work or model establishing the relation been personality or user requirement and desirability or adaptability.

Existing assistive technologies deployed in e-learning environments for sighted users have their limitations anchored to the aforementioned discussions. The multi-model developed based on Artificial Neural Network (ANN) for e-learning focused on estimation-based learning. This lack exactness calibration of learners (Paramythis and Loidl-reisinger, 2004). In this estimation-based learning, the presentation of learning content was not considered. The work of Villaverde *et al*. (2006) addressed this limitation by developing ANN-based presentation model for e-learning content. With this enhanced content presentation, the learning activities in e-learning environment improved.

However, insensitivity to the specific user's need emerged as the major limitation of the work by Villaverde *et al*., (2006). In order to mitigate this challenge, adaptation of layout of e-learning environment was introduced by the work of Al-Badowi (2010). The introduction of learning layout adaptation attained improved layout that best fits user's needs. The adaptation is, however, limited to environmental layout adjustment to address user's requirement. This does not include adaptation of the content of a specific layout. This work was improved upon by Ruokonen and Ruismäki (2016). Adaptation of e-learning content was integrated into the existing model. This improvement achieved adaptation based on e-learning domains.

The inherent weakness of the contribution by Ruokonen and Ruismäki (2016) is lack of consideration for specific users in each domain. Christ and Thews (2016) improved this by developing a domain-based content adaptation for sighted users in e-learning environment and standardisation of learning object. Contributions of the previous work focused mainly on layout and content in e-learning environment. Chaplot (2016) extended the coverage by developing ANN-based adaptive e-learning system architecture. Particularly, this model included concept-based and instruction-based e-learning framework. One major user's requirement that enhances learning is visual capacity. However, the work of Chaplot (2016) and all the previous studies did not consider e-learning users with varying degrees of visual impairment.

2.7.1. Styles of Learning in e-learning Environment

The e-learning's trend is changing; learning content has become the key issue of current e-learning. The e-learning in many countries is not yet so widely used as an alternative to other forms of training: as is the case of traditional classroom. This is because learners do not identify own learning style in the way the presentation of education content are done in the majority of e-learning material produced today, or not feel enough customisation in the content to their own needs (Villaverde *et al.*, 2006).

A description was made by Al-Badowi (2010) on the design, development and implementation of the model of an adaptive course player that uses Kolb learning styles and neural networks to model learners and dynamically generates navigation paths and layout adaptation. The system implements adaptation of individual recommendations and content adaptation based on learning styles, previous learner knowledge, learner's progress and persistence of their own preferences (Al-Badowi, 2010). Experiences of students using the e-learning platform were used in producing e-learning content and an actual e-learning project to evolve the way difficult domain content can be presented to different individuals or stereotyped groups (similar conceptual understanding) with a disparity of objectives, different kind of professional roles, dissimilar previous knowledge and different context (Ruokonen and Ruismäki, 2016).

Modern developments in the field of content standardisation for learning objects and metadata (LOM, SCORM) open new possibilities for adaptive educational media to work with masses of content and learning objects (Christ and Thews, 2016). The appropriate modelling of the learner's needs and preferences, representation of pedagogical strategies, learning designs and assets as well as the runtime reconciliation of these elements, are the key issue for next generation e-learning. This can be done with the help of some kind of learning styles classification and a mechanism to produce personalised content (Zare *et al*., 2016).

2.7.2. Modelling Student Learning Styles with Feed Forward Neural Network

The mapping between students' actions in e-learning system and the learning style that best fit them was carried out using feed forward neural network architecture. To achieve this goal, the inputs of the network, its output and the meaning of their possible values were identified. The other necessary architectural parameters determined were the number of hidden layers, the number of processing units in each hidden layer, the activation function in each processing unit and the learning coefficient of the network (Villaverde *et al*., 2006).

In order to represent the input of the network, Gonsalves and Dougherty, (2006) used one processing unit (neuron) in the input layer per observed action in the system. The actions are as follows:

1. Reading material: academic units can be presented using both abstract (theories) and concrete material (exercises). What kind of material is the student most interested in?
2. Access to examples: in each academic unit, a number of examples are presented to students. In relation to the total number of available examples, how many of them has the student accessed to?
3. Answer changes: Does the student change the answers of the exam before he hands it over? If yes, what is the percentage of answers he has changed?
4. Exercises: a number of exercises are also included in academic units. In relation to the total number of available exercises, how many exercises has the student accessed to?
5. Exam delivery time: each exam has an associated time to be solved. What is the relation between the student's exam delivery time and the units' time to solve?
6. Exam revision: in relation to the time to solve of the exam, what was the percentage of time spent by the student checking the correctness of the exam?
7. Chat usage: the student may ignore the chat, read other students' messages or read/write messages with others.

8. Forum usage: the student may ignore the forum, read other students posted messages or post messages in the forum.
9. Mail usage: the student may use (or not) the e-mail.
10. Information access: information in academic units is presented following a line of reasoning. How has the student followed that line of reasoning? Line-ally, or has he or she visited a random sequence of items?

These input values were encoded in the real interval [- 5, 15] as expected by the neurons in the input layer of the network. The interval was intentionally selected to match the expected domain of the activation function chosen for the units of the network.

In the output layer, the output of the network approximated the learning style of the students based on the actions presented at the input layer. One processing neuron was used in the output layer for each learning style dimension used in the model. Three of the four dimensions of the Felder-Silverman model were used to model students learning style by Graf *et al*. (2007). The dimensions used were:

1. Perception: this dimension determines whether the style of the student is intuitive or sensitive.
2. Processing: this dimension decides whether a student's leaning style better fits active or reflective.
3. Understanding: this dimension informs whether the student learning style is sequential or global.

2.7.3. Neural Network Based Adaptive and Personalised Learning

Adaptive learning is the core technology behind intelligent tutoring systems, which are responsible for estimating student knowledge and providing personalised instruction to students based on their skill level. Adaptive learning refers broadly to a learning process where the content taught or the way such content is presented changes, or "adapts," based on the responses of the individual student (Paramythis & Loidl-reisinger, 2004). It is the core technology for intelligent tutoring systems having 3 major components: model of content to be learned (Content Model), model to estimate student proficiency (Learner Model) and a model to present content to the student in a personalised fashion based on his proficiency (Instructional Model).

Chaplot, (2016) presented a new adaptive learning system architecture using artificial neural network to construct the Learner Model which automatically models relationship between different concepts in the curriculum and beats Knowledge Tracing in predicting student performance. The adaptive learning system overcomes two important shortcomings of existing adaptive learning systems:

1. inability of Learner Model to handle multi concept problems and
2. inability of Instructional Model to systematically select problems of appropriate difficulty for the student to maximise learning gain.

The existing works as the benchmark for this research work are summarised in Table 2.2.

Table 2.2. Baseline Research Work

Author/Year	Achievement	Scope/Limitation	Gap
(Paramythis & Loidl-reisinger, 2004)	Multi-model based ANN e-learning platform	Estimation-based learning	Lacks exactness calibration of learners
(Villaverde et al., 2006)	ANN-based Presentation of learning in electronic form	Content presentation	Lacks customization to user's needs
(Al-Badowi, 2010)	Introduction of adaptations to e-learning	Layout adaptation	Lacks content adaptations
(Ruokonen & Ruismäki, 2016)	Integration of content adaptation	Domain content adaptation	Lack domain users specificity and standardization
(Christ & Thews, 2016)	Improving of domain-based content adaptation for users with standardization	Learning object standardization	lacks learning styles classification
(Chaplot, 2016)	ANN-based adaptive e-learning system architecture	Developed for users for certified healthy to use such platforms; it is concept-based and instruction-based	Lacks consideration for user's visual learning disability

CHAPTER THREE

METHODOLOGY

3.1. General Introduction

In order to mitigate the problem of vision impaired users of multimedia resources with respect to low visual acuity, a dynamically adaptive calibrator was developed based on adaptive calibration parameters. Taking this calibrator as the basis, a dynamic thresholding algorithm for modelling visually impaired users was developed, implemented and evaluated.

The general design or methodology of achieving the objectives of this research work is presented in Figure 3.1. The flow of a block diagram for the parametric indicators was linked to the calibrator setup. The modules of the Dynamic Thresholding Algorithms were linked to the components of the calibrator.

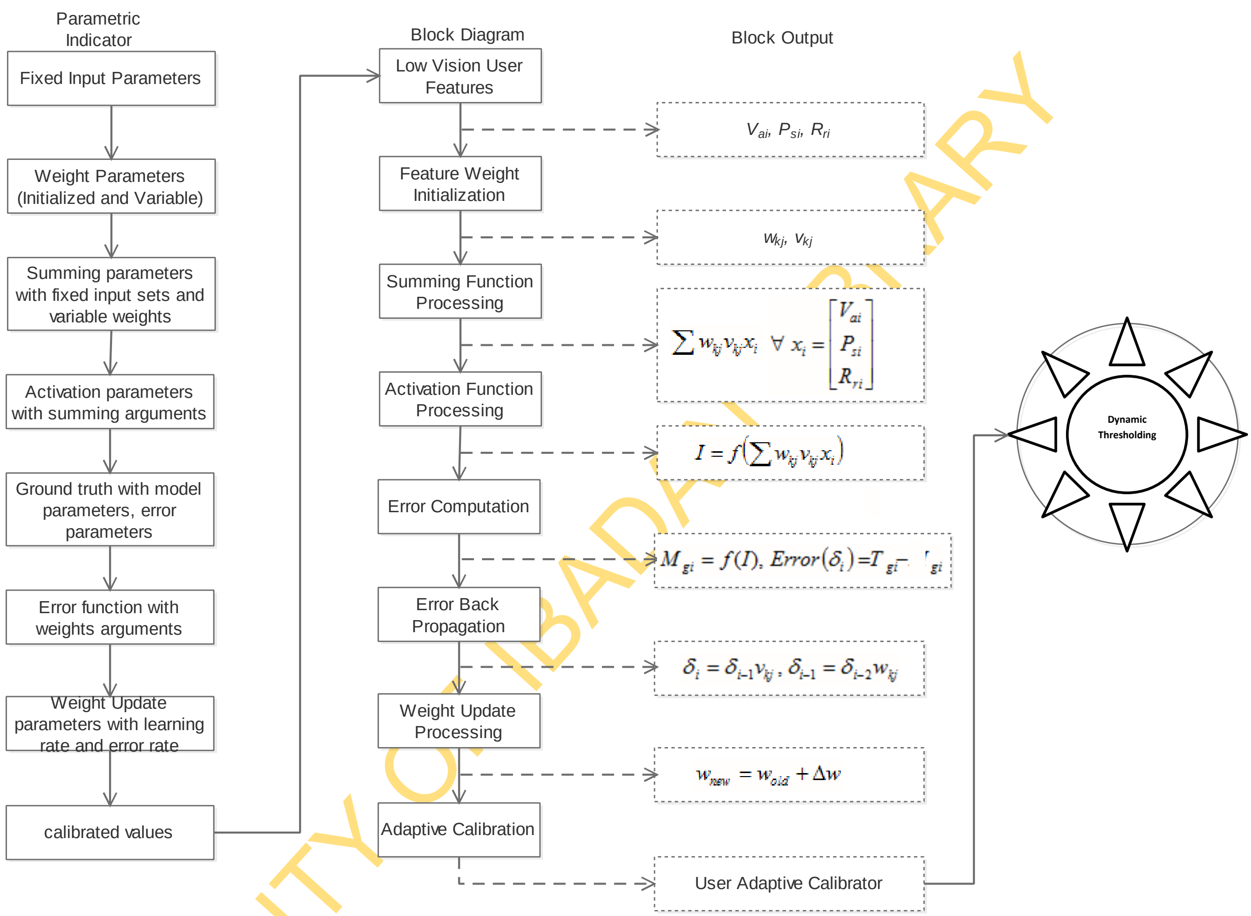

Figure 3.1. Generic Framework of Intelligent Access Model for Vision Impaired Users

3.2. Calibration Parameters for Low Acuity

3.2.1. Introduction

Visual Acuity (VA) or Clarity is measured against an agreed standard under the best conditions. The standard as defined by Snellen is the ability to recognize one optotype when 5 minutes of arc is subtended. Thus, the optotype can only be recognized if the person viewing it can discriminate a spatial pattern separated by a visual angle of one minute of arc. The symbols on an acuity chart are referred to as optotypes. Clear Visual Acuity or seeing details clearly or normal vision is generally defined as “20/20” (in feet) or “6/6” (in metres) vision. Maximum VA or clarity (20/20) only occurs in the central 5 degrees of the visual field. Outside of the central part of the visual field, acuity falls off sharply to 20/200 (6/60). Three factors contributing to low visual acuity are:

1. the users visual system
2. the environment
3. the visual task

The visual system includes the parts of the eye and the visual/perceptual regions of the brain. The eyes function to focus light/images on the retina. In order for the image to resolve its focus on the retina, light must pass through a smoothly curved cornea, pass through a clear fluid, the pupil must let in the right amount of light, pass through a clear lens that can flex to adjust focus, pass through more clear fluid, and arrive at the proper place on the retina that has functioning nerve cells. The light is converted to nerve impulses that travel through various structures in the brain. We "see" when the brain decodes/interprets the signals providing perception and meaning to the light passing through the eye. Anomalies/malfunctions in any or all of these components of the visual system can reduce clarity.

The environment plays an important part in clarity. It includes illumination/lighting, glare, distance, visual field, magnification, viewing angle, and time. The environment may be dynamic/moving, or the user is moving through a static environment, regardless, the visual task also moves. The object may be too far away or too close. The user wants an environment that adds to clarity.

The final factor is the visual task. What is the user trying to "see". The shape and size of the object, spacing in relation to other objects, colour of the object, and contrast with the environmental background are all parts of the visual task. As an example, a common visual task on the web-reading will be used. Given the current functioning of the user's visual system, the current environment, are the letters the "right" size, font, colour?. Are the letters the "right" distance apart to clearly see each letter, are the lines of text the "right" distance apart so they do not merge and are easy to track?. Is there the "right" amount of contrast between the letters and the background?. Is the background too bright/dim or too busy or cluttered?

3.2.2. Effect of Low Acuity in Vision Impaired Users

Clarity problems as with all vision problems exist on a continuum. The user wants to achieve maximum clarity within the dynamics of the visual system, the environment, and the visual task. Each of these is fluid. The visual system changes with time of day, energy level, and other physiological parameters. The environment changes with the range of illumination, type of device, the location of the task, time of day, motion of the task and/or user, and more. The user will change the environment to maximize clarity. The visual task changes with size, colour, contrast and other factors. The user will change the illumination, magnification, viewing angle, distance to the object, colour, etc. to improve clarity. Note, as the user increases the apparent size of content through magnification or zooming the perceptual area is reduced proportionally.

3.2.3. Low Acuity and e-learning

Some of the most common problems faced by students with low acuity include poor accessibility of Web sites, poor accessibility of learning materials and different learning needs due to their acuities. One of the most prominent problems is that e-learning Information Technology courses are specifically not designed for abnormal sighted students. The guidelines for Web accessibility for students with low acuity are not specific enough for the effective design of learning materials for the vision impaired. There is also a misalignment of guidelines for the development of accessible teaching and learning materials and Web accessibility standards and guidelines. Additional teaching aids created specifically for vision impaired students are necessary to ensure the students understand the concepts being taught.

The second problem is that e-learning models are commonly designed for sighted students and do not incorporate considerations for students with disabilities, particularly vision disabilities. Learning outcomes commonly assume that all students are sighted and students with low acuity are expected to attain the same learning outcomes to succeed in the course. More specific and broader communications are required in an e-learning environment for the vision impaired. Without vision, students and teachers use speech to a much greater extent and a virtual classroom is needed to supplement the physical classroom and laboratory setting. There are major differences between the needs of vision impaired students and sighted students. Sighted students are able to access images, diagrams and tables and easily interpret these, whereas vision impaired students are not able to access these at all. e-learning materials are not frequently designed to integrate with the range of assistive technologies used, resulting in vision impaired students receiving incomplete or inaccurate translations, or, at worst, no accessibility at all.

A further problem is that students with low acuity are often isolated by their impairment and e-learning models seldom include considerations of social elements. Vision impaired students need confidence building through the sharing of knowledge and skills. Means of communication on issues including assistive technologies, the technology of the learning environment, learning matters, accessibility and general matters need to be part of the learning environment. Students with a vision disability readily share their knowledge so that the group achieves the learning outcomes, not just the individual. Therefore IT is important, so that students have a ready means of communicating their knowledge within the group.

A final problem is that teachers seldom understand the needs of vision impaired students and the barriers to learning these students face. Teachers need to know how to solve learning problems that relate to vision disabilities; they need to understand not only assistive technologies, but also how to work around inaccessible features of the curriculum and the learning environment. An understanding of the needs of vision impaired students is an essential component when designing an effective and accessible e-learning environment.

3.2.4. Adaptive Calibration Parameter

The visual acuity calibrator has some variable parameters that enhance the adaptiveness of the calibration. The parameters are input variables, weights, biases, activation functions in the hidden and output layers. Target parameters are the expected output used for supervised learning approach in this research work.

3.2.4.1. Simple Graphical Model

The diagram for Adaptive Calibration Parameter Model is shown in Figure 3.2. It consists of three input variables which are Visual Acuity, Print Size and Reading Rate. The input parameters are linked to ten neurons in the hidden layer using weighted connections. The connections were weighted using adjustable weight and bias parameters. The weighted inputs were summed using summing function. As shown in Figure 3.2, the sums of weighted inputs were activated using activation or transfer functions. The result of activation function in the hidden layer was transferred as input to the neurons in the output layer. Actions similar to the processes performed in the neurons in the hidden layer were carried out in the neurons in the output layer. Three-bit outputs were used as binary encoded outputs as clearly shown in the diagram.

The importance of appropriate parametric definition for visually impaired users cannot be overemphasized. Figure 3.2 gives our model for determining the parameters based on user identity. Essentially, this model presents the Input parameter, Adjustable weight parameters, Summing function, Activation function, Numbers of neurons and Adjustable Biases for the desired output. In section 3.2.4.2, each of these parameters is defined and their effects on the overall performance of the model.

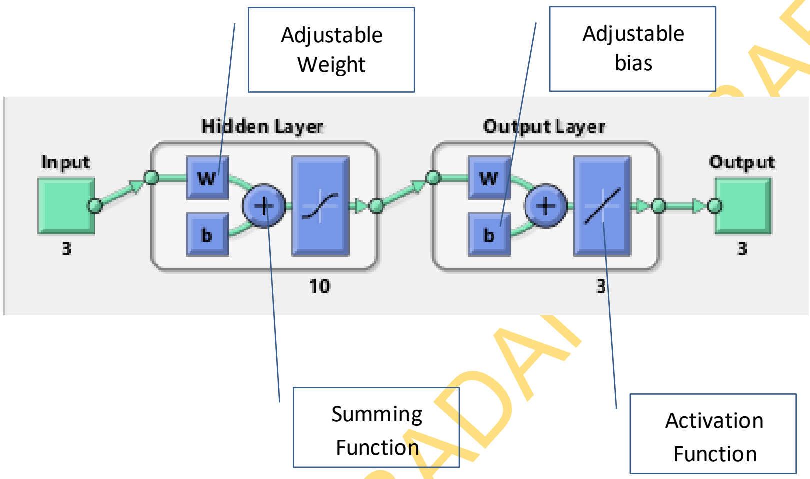

Figure 3.2. Adaptive Calibration Parameter Model

3.2.4.2. Definition of Parameters

Input parameters:

Visual Acuity (V_a): This is a measure of person's central vision and the ability to distinguish details and shapes of objects. It is the ratio of 1 to gap size (arc min), expressed as,

$$Acuity = \frac{1}{gap\ size[arc\ \min]}$$

Print Size (P_s): This is the size of the printed text. It is the text height between the base line and the ascender line. *Base line* is the imaginary line upon which the text lies while *ascender line* is the imaginary top boundary. Also, print size connotes the text height between the *x*-line and descender line. The inner top boundary line is the *x-line* while *descender line* is the lower boundary.

Reading Rate (R_a): Reading rate is part of the broader umbrella of fluency and is measured in words read per minute.

The input parameters are fed into a neuron in ANN-based model as Figure 3.3.

Weight parameters:

Connection Weights (w_{kj}, v_{kj}): there two categories of weights – Input Weights and Layer Weights.

Input Weights: The connections between the input nodes and the hidden layer are associated with weights denoted by w_{kj}.

Layer Weights: The notation (v_{kj}) is used to denote connections between the hidden layer and the output layer. Both weights are proportional to the number of neurons in the hidden and output layers.

The weight parameters are initialized as shown in Figure 3.4.

Summing function parameters:

Summer (S): This is an adder of the weighted input values. It exists in each neuron both in the hidden layer and output layer. The processes of the adder are depicted in Figure 3.5.

Activation function parameters:

Transfer (I): This is a normalising function that normalises the summed weighted inputs into the model output. This is depicted in Figure 3.6.

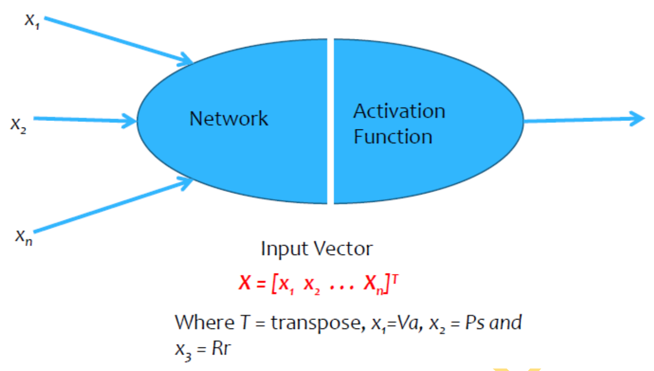

Figure 3.3. Input parameters to a neuron

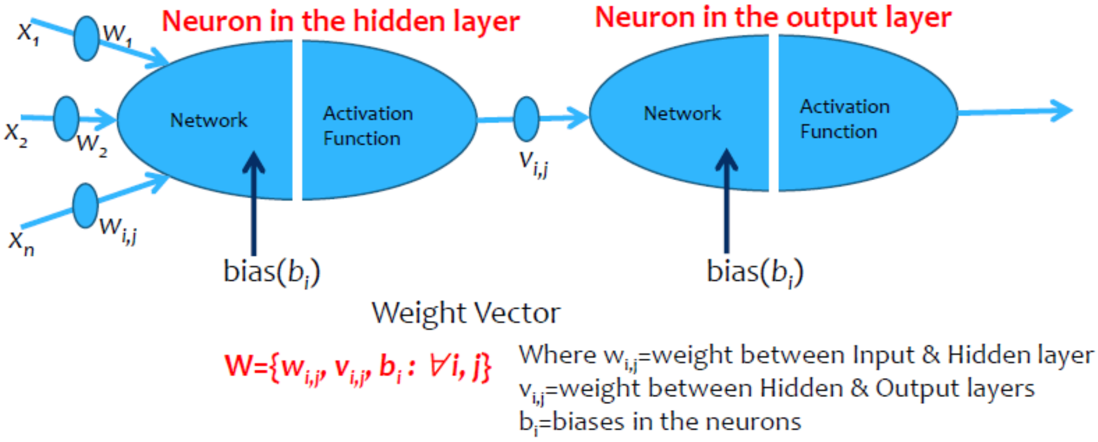

Figure 3.4. Weight and bias initialization

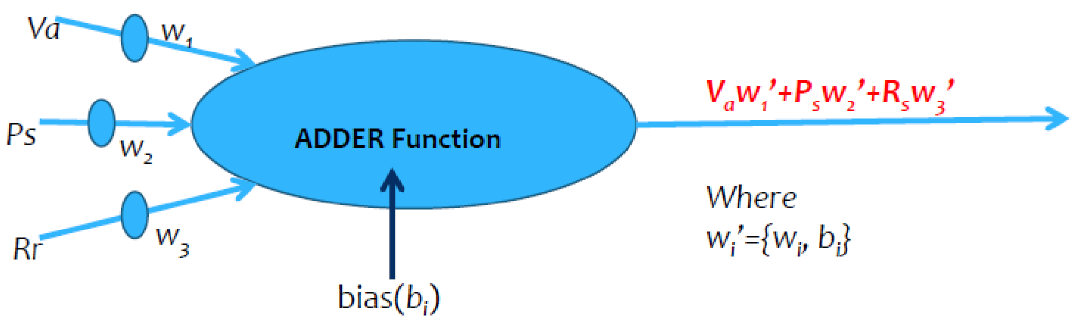

Figure 3.5. Summing parameters

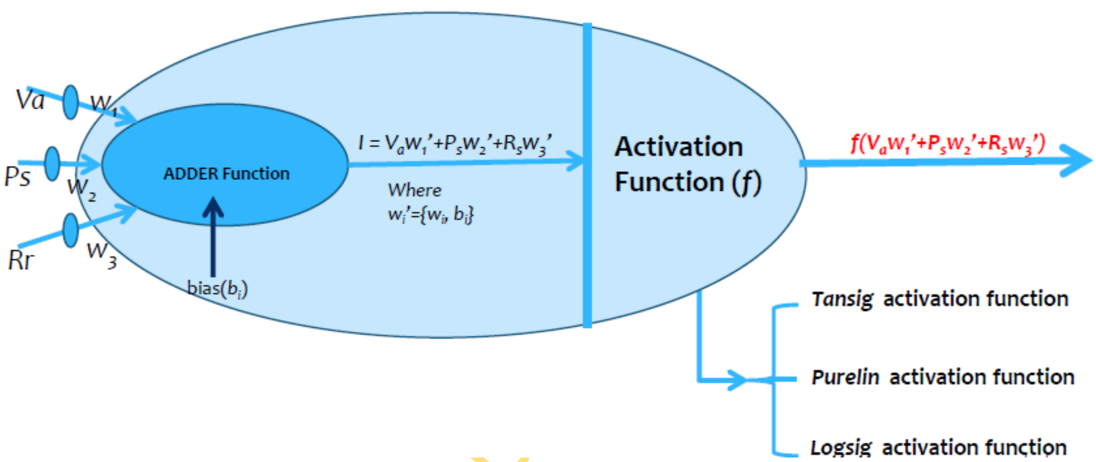

Figure 3.6. Activation function parameters

Error computation parameters:

Model grouping (M_g): This is the calibrator grouping of the input features (V_a, P_s, R_a) associated with weights

Target grouping (T_g): This is the actual grouping of the input features

Error (δ): This is the deviation of the Model grouping from the Target grouping. The error computation is shown in Figure 3.7.

After the error has been computed, it is propagated backward using backpropagation algorithm. This procedure is depicted in Figure 3.8.

After propagating the error backward, then the weight is re-computed in order to get weight update. With the weight update, feedforward supervised processing is continued. This is shown in Figure 3.9.

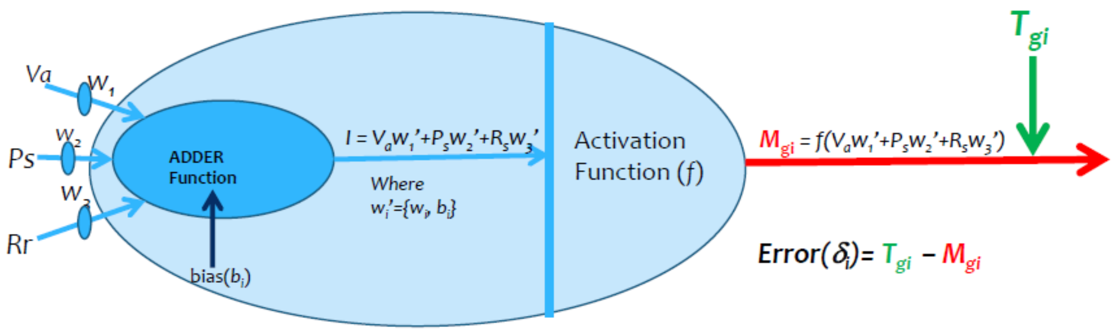

Figure 3.7. Error computation

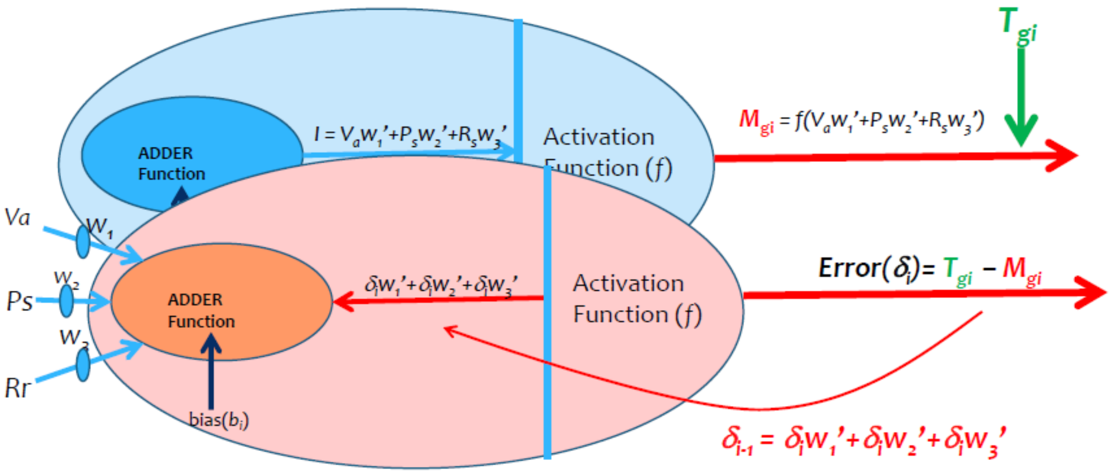

Figure 3.8. Error Backpropagation

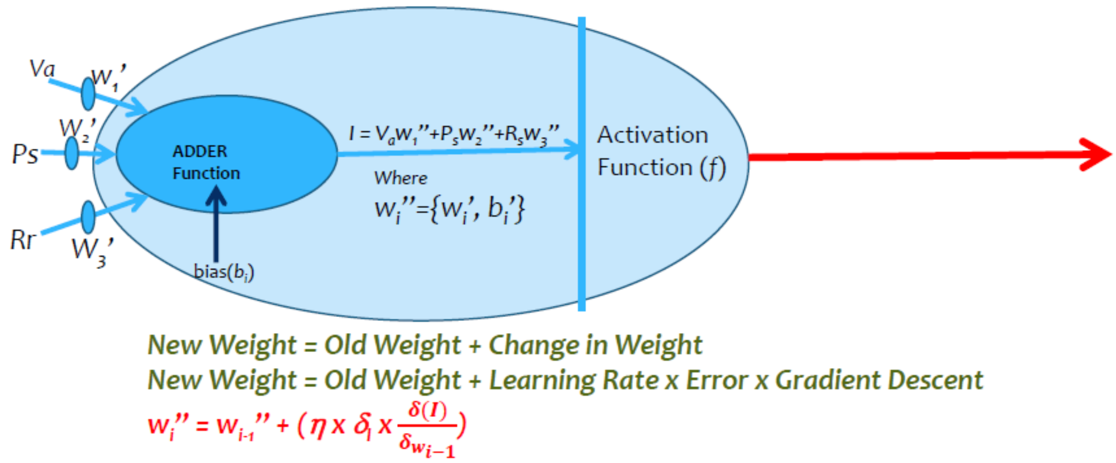

Figure 3.9. Weight update processing

3.3. Adaptive Calibrator for Vision Impaired Users

Vision impaired users have different categories of visual impairment. Proper categorization of such users is needed in order to mitigate visual challenges in e-learning environment. The developed calibrator in this research work essentially has three input features. The calibrator was developed using modified artificial neural network which intelligently and adaptively categorizes visual impaired users in e-learning environment. The architecture of the adaptive calibrator is shown in Figure 3.3.

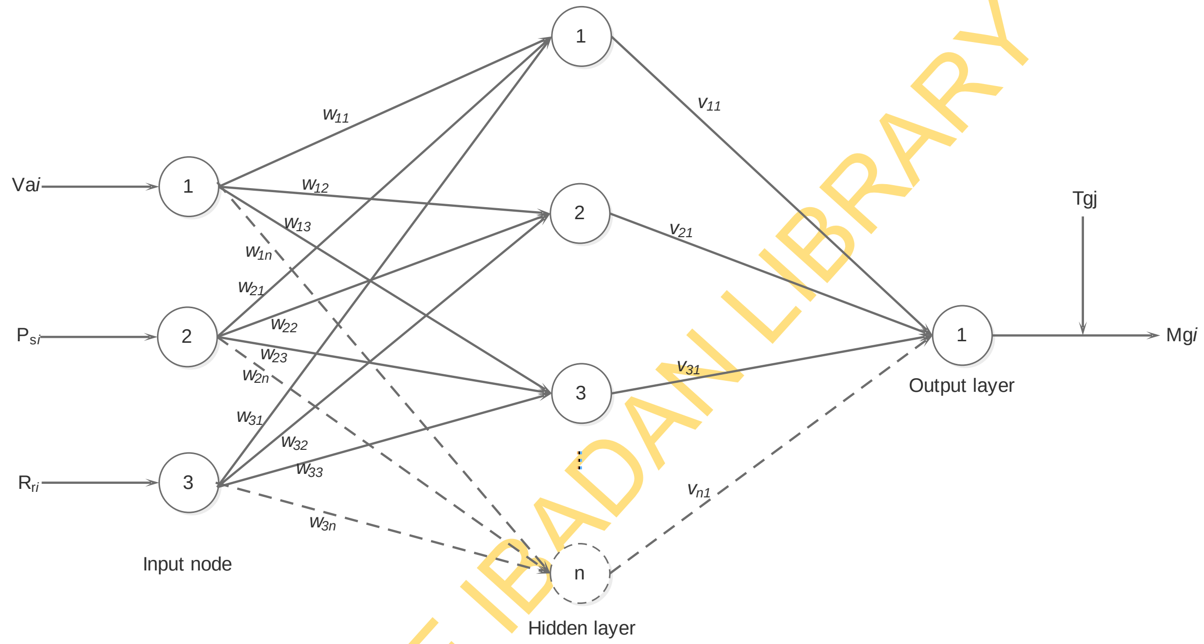

Figure 3.10. Adaptive Calibrator Architecture

3.3.1. Vision Impaired Users and their Characteristics

3.3.1.1. Characteristics

Visual impairment is essentially an umbrella term used to describe the loss of sight that can be a consequence of a number of different medical conditions. Some common causes of visual impairment are glaucoma, retinopathy of prematurity, cataracts, retinal detachment, macular degeneration, diabetic retinopathy, cortical visual impairment, infection and trauma. These are just a handful of dozens of conditions impacting sight, and each condition has its own unique characteristics and clinical features. In addition, the impact of the visual impairment on individual learning is also tied to the onset, the severity, and the type of visual loss, as well as to any coexisting disabilities that may be present in the student. For this reason, all classroom accommodations, modifications, and strategies must be designed with the individual needs of each student with a visual impairment in mind. There is no one-size-fits-all model.

In addition to decreased visual acuity and visual field, a number of other vision problems may also impact the visual functioning of the student with visual impairment. There may be issues with sensitivity to light or glare, blind spots in their visual fields, or problems with contrast or certain colours. Factors such as lighting, the environment, fatigue, and emotional status can also impact visual functioning in many of these students throughout the day. Students who have the same visual condition may use their sight quite differently. To ensure accessibility to classroom instruction, it is essential that you know how each student is using his/her vision.

3.3.1.2. Impact on Learning

One characteristic that is shared by all students with visual impairment is that these students have a limited ability to learn incidentally from their environment. It is through sight that much of what is learnt is received and processed. The other senses do not fully compensate for the loss of sight. Touch and hearing can be ineffective substitutes for many individuals.

Students with visual impairments must be taught compensatory skills and adaptive techniques in order to be able to acquire knowledge from methods other than sight. The presence of a visual impairment can potentially impact the normal sequence of learning in social, motor, language and cognitive developmental areas.

Reduced vision often results in a low motivation to explore the environment, initiate social interaction, and manipulate objects. The limited ability to explore the environment may affect early motor development. These students cannot share common visual experiences with their sighted peers, and therefore vision loss may negatively impact the development of appropriate social skills. As a result, these students may experience low self-esteem that limits their sense of mastery over their own lives.

It is not enough to just provide instruction in the general core curriculum. Students with visual impairments also need specialised instruction in a number of other essential skill areas. These areas, called the expanded core curriculum, include communication skills, social interaction skills, orientation and mobility, independent living skills, recreation and leisure skills, use of assistive technology, visual efficiency, and career education skills, and self-determination. Mastery of these skills is essential for students' long-range educational and life outcomes. Students with visual impairments can learn at roughly the same rate as other children but require direct interventions to develop understanding of the relationships between people and objects in their environment.

3.3.1.3. Teaching Strategies

Classroom accommodations should be quite varied and individualised according to the specific needs of the student. However, there are some basic best practices that can guide the development of the most effective adaptations. One thing to always consider is that it is often difficult for these students to become as fully independent as they are capable of being. The classroom teacher should encourage independence as often as possible to avoid the trap of "learned helplessness." Materials, desks, and other objects in the classroom should be maintained in consistent locations. Part of becoming independent for students with a visual impairment is learning when to advocate for assistance. Not all instructional tasks will be immediately possible for a student with a visual impairment, even with accommodations. The key is to design instruction so that the student has the most opportunity to act independently. The student's orientation and mobility specialist and teacher of students with visual impairments can assist with room arrangements and room familiarisation.

Adapting classroom to accommodate a student with a visual impairment is a relatively easy task, it just requires an awareness of the student's level of visual functioning (how the student sees) and how the student works and learns. For example, for the student with vision impairment, make sure that he is near the front of the room where he can see the blackboard. Control lighting variables when presenting learning materials to those students who are sensitive to light and glare. Use verbal cues with those students who cannot see body movements or physical cues. A trained teacher of students' visual impairments can help to make a few simple changes to classroom design that may mean all the difference in the education of the student with a visual impairment.

One key accommodation that is absolutely essential is access to textbooks and instructional materials in the appropriate media and at the same time as their sighted peers. For students who are blind this may mean braille and/or recorded media. For the student with vision impairment, this may mean large print text or the use of optical devices to access text and/or recorded media while in class. Working closely with a student's teacher of students with visual impairments in advance helps ensure accessible materials and availability of these materials in a timely manner.

3.3.1.4. Assistive Technology

In order to access print information, students with visual impairments must be trained in the use of a number of adaptive devices, methods, and equipment that are collectively referred to as assistive technology. Some of this technology allows access to information presented on a computer while others are devices to be used independently. Computer hardware and software are continuously advancing, allowing for more access to information than ever before. Some examples:

Computer adaptations:

- Braille translation software and equipment: converts print into braille and braille into print.
- Braille printer: connects to a computer and embosses braille on paper.
- Screen reader: converts text on a computer screen to audible speech.
- Screen enlargement software: increases the size of text and images on a computer screen.

- Refreshable braille display: converts text on computer to braille by an output device connected to the computer.

Adaptive devices:

- Braille note takers: lightweight electronic note-taking device that can be connected to a printer or a braille embosser to produce a printed or brailled copy.
- Optical character reader: converts printed text into files on a computer that can be translated into audible speech or Braille with appropriate equipment and software.
- Electronic braillewriter: produces braille, translates braille into text or synthetic speech.
- Talking calculators: calculates with voice output.

Optical devices:

- Closed Circuit Television (CCTV): enlarges an image to a larger size and projects it on a screen
- Magnifiers: enlarges images
- Telescopes: used to view distant objects

A specially trained teacher can help supply many of these devices and can provide training for the student to become independent and proficient in using assistive technology.

3.3.2. Problem Associated with Vision Impairment

Vision impairment is a situation where human sight is below the normal eye sight for a normal human being. This situation prevents proper and adequate interpretation of visual contents. With regards to e-learning, vision impairment largely hinders effective learning and assimilation of visual-content based learning. Moreover, persistent stress to the eyes without corrective measures for the vision impairment could cause a permanent damage to eye sights generally.

3.3.3. Adaptive Calibrator Model

3.3.3.1. Activation Function Combination Model

The processes involved in the Adaptive Calibrator Model start with Vision Impaired User Features. These features are fed into the calibrator. After accepting the features, weights are randomly fixed between the value of zero and one in the Feature Weight Initialisation. This process is then followed by Summing Function Processing. This is where the weighted input features of visual acuity, print size and reading rate are summed together. Activation Function Processing block consists of three possible function parameters each in the Hidden Layer (*HL*) and Output Layer (*OL*). The three activation function parameters are:

1. Tansig Activation Function

This is hyperbolic tangent sigmoid transfer function. It consists of exponential function of values ranging from negative one to positive one along *y*-axis across positive and negative values of *x*-axis. The function is primary computed as:

$$y = Tansig(x) = \frac{2}{\left(1 + e^{-2x}\right)^{-1}} \tag{3.1}$$

2. Purelin Activation Function

This is a linear transfer function that consists of positive and negative values along *y*-axis across positive and negative values of *x*-axis. The function is computed using a linear function passing through the origin zero with gradient one. Mathematically, this function is generically denoted as:

$$y = kx \tag{3.2}$$

Where k is a constant value

3. Logsig Activation Function

This log-sigmoid transfer function is an exponential-based function that spans from zero to positive one across positive and negative values of *x*. The implication of this function is mapping of input values either positive or negative into positive values only. Any input value(s) that may map into negative values are tailed off to be zero value(s). Mathematically, Logsig Activation Function is computed using:

$$y = \frac{1}{1 + e^{-x}} \tag{3.3}$$

The next processing block is Error Computation. The calibrator compares the model output with the targeted results during the supervised learning stage to determine the error of the calibration. This error is iteratively and dynamically reduced through backpropagation algorithm in the Error back propagation block. Since the value of the weighted features consists of Low Acuity User Features that are constant and associated weights that are variable, the weights are adaptively adjusted in order to reduce the error in Weight Update Processing block. The overall output of these block processing is given in Adaptive calibration block.

The mathematical notation for hidden layer is given as:

$$\begin{aligned} z_i &= x_i \cdot w_{ij} + b_j \\ Z &= \sum x_i w_{ij} + b_j \end{aligned} \tag{3.4}$$

where b_j = hidden layer bias

The mathematical notation for output layer is given as:

$$\begin{aligned} y &= z_j v_j + c_j \\ &= v_j\left(w_{ij} x_i + b_j\right) + c_j \\ &= LW\left(IW \cdot X + B_j\right) + C \end{aligned} \tag{3.5}$$

The generic model is given as:

$$y = AF_{OL}\left(LW \cdot AF_{HL}\left(IW \cdot X + B_j\right) + C\right) \tag{3.6}$$

where AF_{OL} = Activation Function of Output Layer

AF_{HL} = Activation Function of Hidden Layer

X = Input Matrix

LW = Layer Weights Matrix

IW = Input Weights Matrix

B_j = Hidden Layer Bias Matrix

C_j = Output Layer Bias Matrix

The instantiated generic model for Tansig – Purelin Activation Function Combinations is given as:

Recall: The activation function of Tansig is given as:

$$Tansig(x) = \left[\frac{2}{1+e^{-2x}} - 1\right] \tag{3.7}$$

$$Tansig\left(IW \cdot X + B_j\right) = \left[\frac{2}{1+e^{-2\left(IW \cdot X + B_j\right)}} - 1\right] \tag{3.8}$$

$$y = Purelin\left(LW \cdot \left[\frac{2}{1+e^{-2\left(IW \cdot X + B_j\right)}} - 1\right] + C\right) \tag{3.9}$$

The activation function of Purelin is given as:

$$Purelin(x) = k_i x_i \tag{3.10}$$

$$Purelin(x) = K \cdot X \tag{3.11}$$

Therefore, the generic model for Tansig – Purelin Activation Function Combinations is given as:

$$y = K\left(LW \cdot \left[\frac{2}{1+e^{-2\left(IW \cdot X + B_j\right)}} - 1\right] + C\right) \tag{3.12}$$

3.3.3.2. Mathematical Model

The general computations of Adaptive Calibrator Model are mathematically depicted as follows:

$$x_q = \left[x_{q1}, x_{q2}, \ldots, x_{qn}\right]^T \ (q = 1, 2, \ldots, m) \tag{3.13}$$

where x_q = transposed input vectors of the visual impaired features

$$t_q = \left[d_{q1}, d_{q2}, \ldots, d_{qm}\right]^T \ (q = 1, 2, \ldots, m) \tag{3.14}$$

where t_q = transposed expected output or target vectors

Let the output of the calibrator be y_{qi}, Error be E_q and the general error be E,

$$E_q = \frac{1}{2}\sum_{i=1}^{m}\left(t_{qi} - y_{qi}\right)^2 \tag{3.15}$$

$$E = \sum_{q=1}^{q} E_q = \frac{1}{2}\sum_{q=i}^{q}\sum_{i=1}^{m}\left(t_{qi} - y_{qi}\right)^2 \tag{3.16}$$

The gradient descent is computed as in (3.17),

$$\frac{\partial y_k}{\partial w_{ij}} = \frac{\partial y_k}{\partial h_i} \cdot \frac{\partial h_i}{\partial w_{ij}} \tag{3.17}$$

Based on back propagation algorithm, the accumulated error was used to adjust u_{ik} in order to minimise the general error. The learning rate is denoted by μ. The weight update of the output layer weights is given in (3.18):

$$\begin{aligned}\Delta u_{ik} &= -\mu \frac{\partial E}{\partial u_{ik}} \\ &= -\mu \frac{\partial E}{\partial N_i}\frac{\partial N_i}{\partial u_{ik}} \\ &= \sum_{q=1}^{q}\sum_{i=1}^{m}\mu\left(t_{qi}-y_{qi}\right)f_o^{'}(N_i)h_k\end{aligned} \tag{3.18}$$

The error signal δ_{yi} is given in (3.19)

$$\begin{aligned}\delta_{yi} &= -\frac{\partial E_q}{\partial N_i} \\ &= \sum_{i=1}^{m}\left(t_{qi}-y_{qi}\right)f_o^{'}(N_i)\end{aligned} \tag{3.19}$$

The changes in the weights of the hidden layer is in (3.20),

$$\begin{aligned}\Delta w_{ij} &= -\mu \frac{\partial E}{\partial w_{ij}} \\ &= \sum_{q=1}^{q}\sum_{i=1}^{m}\mu\left(t_{qi}-y_{qi}\right)f_o^{'}(N_i)u_{ik}\, f_h^{'}(N_k)x_j\end{aligned} \tag{3.20}$$

3.3.3.3. Algorithm

The algorithm for this calibrator is shown in the Table 3.1. At line 1, the features of a visual impaired user are fed into the calibrator. The neurons in the hidden and output layers are looped to a specified number at an appropriate step size at lines 2 and 3. Within these loops, the weights are randomly iterated from – 1 to + 1. Within lines 7 and 18, generic activation function model are computed over three activation functions (tansig, logsig and purelin) until global minimum mean squared error is arrived at in lines 14 to 17.

Table 3.1: Calibration Algorithm

Input: V_{ai}, P_{si}, R_{ri}

Output: *Adaptive Calibrator*

1: *Entering User Input Features as Column Vector:* $x_i = \begin{bmatrix} V_{ai} \\ P_{si} \\ R_{ri} \end{bmatrix}$

2: *For NoOfNeurons = InitialNeuron To FinalNeuron StepSize*

3:     *For k,j = 1 To NoOfNeurons*

4:         *Random Weight Initialization within range [-1,1]*

5:         *WeightedUserInputFeatures* = $w_{kj}v_{kj}x_i$ || w_{kj}=*Input weights,* $v_{k,j}$=*Layer Weights*

6:         *SumOfWeightedUserInputFeatures* = $\sum_{i=1,k=1,j=1}^{n} w_{kj}v_{kj}x_i$

7:         *While TransferFunc = Tansig, Logsig, Purelin Do*

8:             *ActivationFunc* = $f\left(\sum_{i=1,k=1,j=1}^{n} w_{kj}v_{kj}x_i\right)$

9:             *Model Grouping Computation*

10:             *Error Computation*

11:             *While Error <> 0 Do*

12:                 *Back Propagation of Error*

13:             *EndWhile*

14:             *Do Until MSE global minimum*

15:                 *Weight Update Processing*

16:                 *Feed Forward processing Until 1000 epochs*

17:             *EndDo*

18:         *EndWhile*

19:     *EndFor*

20: *EndFor*

21: *Adaptive Calibrator*

3.4. Dynamic Thresholding Algorithm for Vision Impaired Users

The algorithm used for adaptive Thresholding and search for the best calibration parameters is presented in Table 3.2. This will give several local maxima accuracy values for different Thresholding values. From the parametric learning of the vision impaired users, the global maximum threshold value is used.

3.4.1. Dynamic Thresholding Model

The simple graphical representation for the Dynamic Thresholding Model being developed is depicted in Figure 3.5. Essentially, three major components are conceptualised: the user, the dynamic Thresholding calibrator and the media resources. The Low Acuity User features are made available from ICD-10 of WHO. The major contribution of this research work is on Dynamic Thresholding Calibrator (DTC). The DTC adaptively iterates between four components: Vision Impaired User, Low Acuity/Impairment, Calibration Parameters and Parametric Indicators. All these interface with the accessibility to multimedia resources.

Table 3.2. Dynamic Thresholding Algorithm

Input: *Training and testing datasets*

Output: *Set of thresholds, accuracy, mean, deviation, group detection and group classification*

Input and output features entering
Features transpose preprocessing
While ThreshVal *>= 0.4 Step 0.0005 Do*
    While *AccuracyInstances <= SelectedNoOfRun* ***Do***
        Feedforward NN parameters entering
        NN training output processing
        Error and performance computation
        Simulation with transposed input features
        SimulationResults thresholding with ***ThreshVal***
        Computation of Detection Rate and Classification Accuracy
    EndWhile
    ThreshVal *=* ***ThreshVal*** *+ 0.0005*
    Set of ThreshVal, Accuracy, Mean and Deviation
EndWhile ThreshVal=0.6
For *Optimum Thresholds* ***Then***
    Recal simulated network
    Simulate with test dataset input
    Process simulation results
    Performance of model grouping and target grouping
    Thresholding simulation with Optimum Thresholds
    Group detection processing
    Group classification processing
    Computation of detection rate and classification accuracy
EndFor

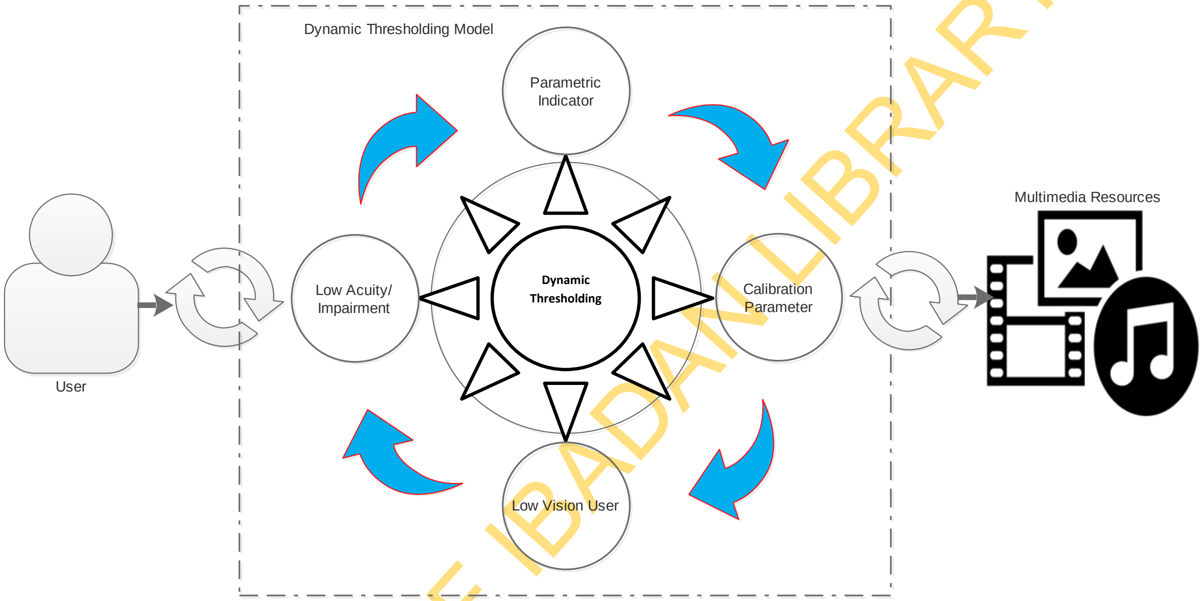

Figure 3.11. Diagram for Dynamic Thresholding Model

3.4.2. Mathematical Model

The $3 \times n \times 3$-ANN model is shown in Figure 3.6. This means 3-input by *n*-hidden layer by 3-output layer. The 3-input component was used to capture the three input features of the vision impaired users. The *n*-hidden layer has *n* variable number of neurons in the hidden layer. Three neurons in the output layer were used for the 3-bit encoded output of the model.

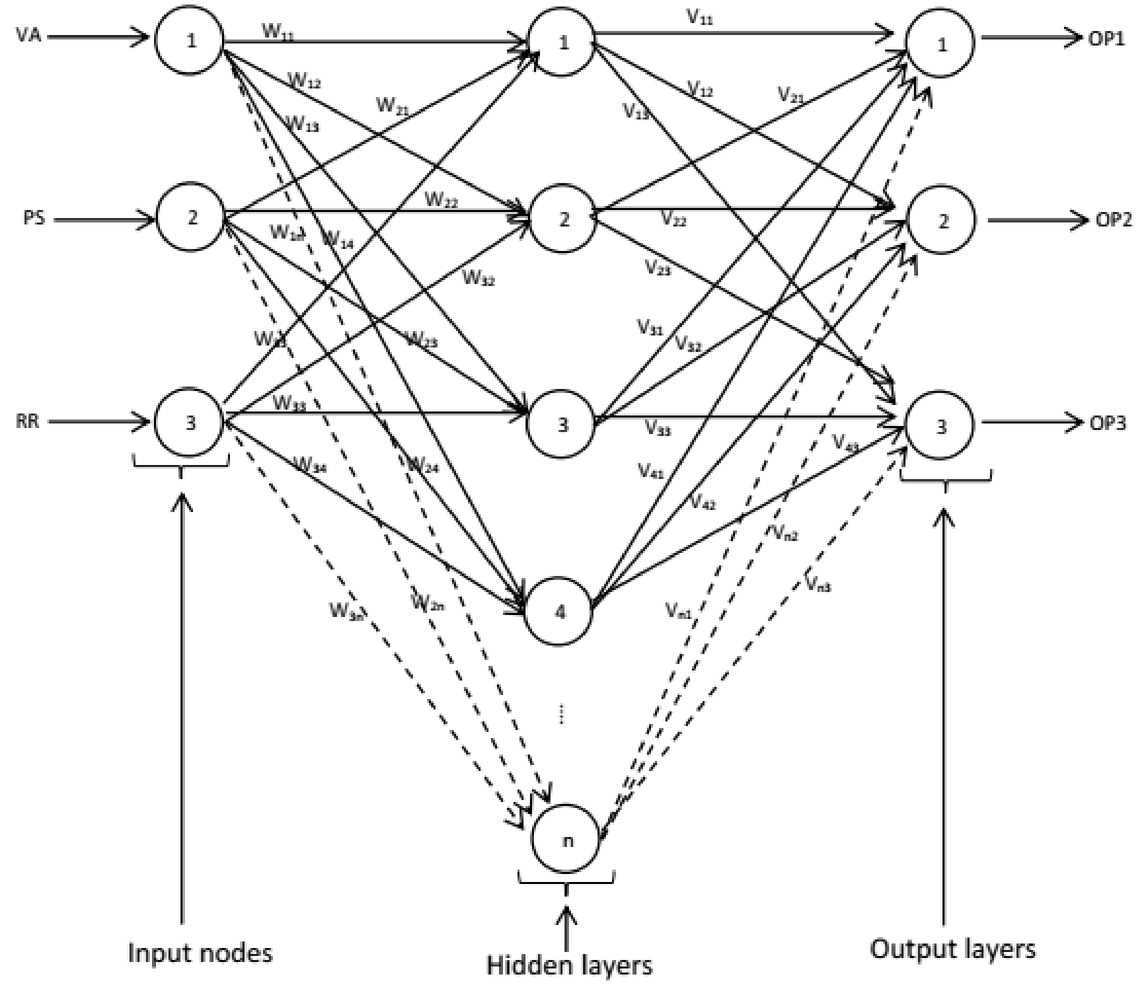

Figure 3.12: $3 \times n \times 3$-ANN Feed-Forward Model Diagram

From the model diagram in Figure 3.6, the input and output matrix equations can be written as:

$$\text{Input} = \begin{bmatrix} Va \\ Ps \\ Rr \end{bmatrix} \tag{3.21}$$

Where Va = Visual Acuity, Ps = Print Size and Rr = Reading Rate

$$\text{Output} = \begin{bmatrix} OP1 \\ OP2 \\ OP3 \end{bmatrix} \tag{3.22}$$

Where OP1, OP2 and OP3 are binary encoded Visual Acuity groups

The equations (3.21) and (3.22) can be combined to form linear equation (3.23)

$$\begin{bmatrix} OP1 \\ OP2 \\ OP3 \end{bmatrix} = [Weights] \begin{bmatrix} Va \\ Ps \\ Rr \end{bmatrix} \tag{3.23}$$

$$\text{Weights} = [w_{ij}][v_{ij}] \tag{3.24}$$

Where w_{ij} are the weights between the input nodes and neurons at the hidden layers and

v_{ij} are the weights between the neurons at the hidden layers and the output layers

The expanded weights equations are given in (3.25) and (3.26)

$$w_{ij} = \begin{bmatrix} w_{11} & w_{12} & w_{13} & w_{14} & \cdots & w_{1n} \\ w_{21} & w_{22} & w_{23} & w_{24} & \cdots & w_{2n} \\ w_{31} & w_{32} & w_{33} & w_{34} & \cdots & w_{3n} \end{bmatrix} \tag{3.25}$$

$$v_{ij} = \begin{bmatrix} v_{11} & v_{12} & v_{13} \\ v_{21} & v_{22} & v_{23} \\ v_{31} & v_{32} & v_{33} \\ v_{41} & v_{42} & v_{43} \\ \vdots & \vdots & \vdots \\ v_{n1} & v_{n2} & v_{n3} \end{bmatrix} \tag{3.26}$$

By substituting all equations (3.24), (3.25) and (3.26) into equation (3.23), it gives equation (3.27),

$$\begin{bmatrix} OP1 \\ OP2 \\ OP3 \end{bmatrix} = \begin{bmatrix} w_{11} & w_{12} & w_{13} & w_{14} & \cdots & w_{1n} \\ w_{21} & w_{22} & w_{23} & w_{24} & \cdots & w_{2n} \\ w_{31} & w_{32} & w_{33} & w_{34} & \cdots & w_{3n} \end{bmatrix} \begin{bmatrix} v_{11} & v_{12} & v_{13} \\ v_{21} & v_{22} & v_{23} \\ v_{31} & v_{32} & v_{33} \\ v_{41} & v_{42} & v_{43} \\ \vdots & \vdots & \vdots \\ v_{n1} & v_{n2} & v_{n3} \end{bmatrix} \begin{bmatrix} Va \\ Ps \\ Rr \end{bmatrix} \tag{3.27}$$

$$= \begin{bmatrix} w_{11}v_{11} + w_{12}v_{21} + \ldots & w_{21}v_{11} + w_{22}v_{21} + \ldots & w_{31}v_{11} + w_{32}v_{21} + \ldots \\ w_{11}v_{12} + w_{12}v_{22} + \ldots & w_{21}v_{12} + w_{22}v_{22} + \ldots & w_{31}v_{12} + w_{32}v_{22} + \ldots \\ w_{11}v_{13} + w_{12}v_{23} + \ldots & w_{21}v_{13} + w_{22}v_{23} + \ldots & w_{31}v_{13} + w_{32}v_{23} + \ldots \end{bmatrix} \begin{bmatrix} Va \\ Ps \\ Rr \end{bmatrix} \tag{3.28}$$

In this research work, the developed 3-bit outputs mathematical model are in equations (3.29), (3.30) and (3.31)

$$OP1 = (w_{11}v_{11} + w_{12}v_{21} + \ldots + w_{1n}v_{n1})Va + (w_{21}v_{11} + w_{22}v_{21} + \ldots + w_{2n}v_{n1})Ps + (w_{31}v_{11} + w_{32}v_{21} + \ldots + w_{3n}v_{n1})Rr \tag{3.29}$$

$$OP2 = (w_{11}v_{12} + w_{12}v_{22} + \ldots + w_{1n}v_{n2})Va + (w_{21}v_{12} + w_{22}v_{22} + \ldots + w_{2n}v_{n2})Ps + (w_{31}v_{12} + w_{32}v_{22} + \ldots + w_{3n}v_{n2})Rr \tag{3.30}$$

$$OP3 = (w_{11}v_{13} + w_{12}v_{23} + \ldots + w_{1n}v_{n3})Va + (w_{21}v_{13} + w_{22}v_{23} + \ldots + w_{2n}v_{n3})Ps + (w_{31}v_{13} + w_{32}v_{23} + \ldots + w_{3n}v_{n3})Rr \tag{3.31}$$

Equivalently, equations (3.29), (3.30) and (3.31) can be transformed to equations (3.23), (3.24) and (3.25)

$$OP1 = a_1Va + b_1Ps + c_1Rr \tag{3.32}$$

$$OP2 = a_2Va + b_2Ps + c_2Rr \tag{3.33}$$

$$OP3 = a_3Va + b_3Ps + c_3Rr \tag{3.34}$$

where a_i, b_i and c_i, $i=1,2,3$ are constants which coefficients derivable from the ANN-based models developed in MATLab.

The coefficients in equations (3.32), (3.33) and (3.34) are extracted in matrix notation to form equation (3.35),

$$\begin{bmatrix} a_1 & b_1 & c_1 \\ a_2 & b_2 & c_2 \\ a_3 & b_3 & c_3 \end{bmatrix} = [ANN\ model\ weight\ matrix] \qquad (3.35)$$

$$ANN\ model\ weight\ matrix = \left[IW_{ij}\right]' \left[LW_{ij}\right]' \qquad (3.36)$$

where IW_{ij} = Input weight matrix, IL_{ij} = Layer weight matrix

CHAPTER FOUR

RESULTS AND DISCUSSION

The study has developed adaptive calibration parameters and parametric calibrator for low acuity and vision impaired users respectively. Subsequent to these, a dynamic thresholding algorithm for modelling visually impaired users was developed. In this chapter, the implementations of the developed algorithms and model are presented. The level of visual impairment according to the World Health Organisation (WHO) is presented. In line with this, the varied visual acuity range with screen magnification, assistive technology, group and group encoding is given in this chapter. A sampled preprocessed dataset of ICD-10 of WHO with input and output features is presented.

4.1.Data Encoding/Grouping

The visual impairment grouping dataset of the World Health Organisation (WHO) was used. The contrasted grouping is in Table 4.1 and 4.2. The sample of instantiated visual impairment dataset from 2008 to 2013 is in Table 4.3.

Table 4.1. Level of visual impairment and blindness according to the WHO

Level of Blindness		Definition	Implications
0	Mild or no Visual Impairment	Vision better than: 6/18, 3/10, 20/70	May be glasses
1	Moderate Visual Impairment	Vision better than: 6/60, 1/10, 20/200 Vision worse than: 6/18, 3/10, 20/70	Glasses and possible need for magnifiers on computer interface
2	Severe Visual Impairment	Vision better than: 3/60, 1/20, 20/400 Vision worse than: 6/60, 1/10, 20/200	Magnifiers and colour contrasters for computer interfaces
3	Moderate Blindness	Vision better than: Can count fingers @ at 1 meter distance Vision worse than: 3/60, 1/20, 20/400	Strong magnifiers for some but mainly screen readers for computer interfaces
4	Severe Blindness	Vision better than: Light perception Vision worse than: 1/60, 1/50, 5/300	Screen readers for computer interfaces
5	Complete Blindness	No light perception	Screen readers for computer interfaces

Source: http://www.igi-global.com/chapter/elearning-for-persons-with-visual-disabilities/128049

Based on the computation of magnification and recommendations by Legge *et al*. (1992) in conjunction with WHO grouping of visual acuity range, the following screen partition versus magnification ratios are presented in Table 4.2. The Table presents WHO standard range for visual acuity. The magnification ratio provides the basis for the multimedia accessibility of the developed model in this research work. As presented in Table 4.2, three-bit group encoding was used in order to capture binary digit conversion of the six visual acuity range grouping.

In order to feed visual impairment dataset of WHO into the ANN-based modeling process, binary encoding preprocessing of the group was carried out. Since calculation of magnification is based on the first three features, these features were taken as the input features while the category or group was taken as the output of the modeling process as in Table 4.3.

Table 4.2. Visual Acuity Range, Assistive Technology Specification and Group Encoding

Visual Acuity Range (VAR)	Screen Magnification Ratio	Other Assistive Technology	Group	Group Encoding
VAR ≥ 0.3	1	None	1	001
0.1 < VAR < 0.3	2	JAWS	2	010
0.07 ≤ VAR < 0.1	3	JAWS	3	011
0.05 ≤ VAR < 0.07	4	JAWS	4	100
0.02 ≤ VAR < 0.05	6	JAWS/BRAILLE	5	101
VAR < 0.02	9	JAWS/BRAILLE	6	111

Table 4.3. Preprocessed Dataset with Input and Output Features

Input Features			Output
Visual Acuity (Va)	Print Size (Ps)	Reading Rate (Rr)	Group
0.20	21	13	2
0.07	47	16	4
0.09	64	16	3
0.46	30	94	1
0.10	57	11	3
0.49	27	63	1
0.07	14	20	3
0.10	50	19	3
0.09	31	14	3
0.60	34	107	1
0.28	28	95	2
0.03	63	2	5
0.43	21	75	1
0.08	56	10	3
0.06	28	12	4
0.09	61	18	3
0.07	26	11	4
0.45	24	105	1
0.09	60	12	3
0.07	20	19	3
0.08	3	3	3
0.10	59	16	3
0.21	11	3	2
0.03	14	2	5
0.09	30	8	3
0.35	50	93	1
0.19	6	3	2

4.2. Model Performance and Evaluation

The adaptive calibration parameters are input, adjustable weights and biases, summing function, activation function and target output. In a conventional artificial neural network, static activation function is used. For improving vision impaired users calibration, this study developed a dynamic thresholding model based on adaptive calibration parameters with modified artificial neural network. Parts of the modification entail iteration and looping over different activation functions in the neurons in both the hidden and output layers. Consequently, the activation functions in the hidden and output layers are iteratively paired for developing optimised model in order to effectively mitigate the influence of outliers that may lead to misclassification.

4.2.1. Adaptive Calibration Parameters for Low Acuity

The parameters for the adaptive calibrator were iteratively paired in the neurons in the hidden layer and output layer. Three activation functions were paired in the hidden and output layers to form nine pairs as presented in the subsequent sections. The matlab codes for ANN-based model performance and evaluation is in Appendix A.

4.2.1.1. Parametric results for hidden layer purelin activation function and output layer purelin activation function

The activation function in both the hidden and output layers is purelin for this calibration as in Figure 4.1. During the calibration, total of ten iterations were made within 1 second. The gradient descent for the learning rate is 2.73×10^{-7}. Six validation checks were made during the iterations. The calibration converges at the 4th epoch within the 10 epochs recorded. This gives performance of mean squared error of 0.17467 as shown in Figure 4.2.

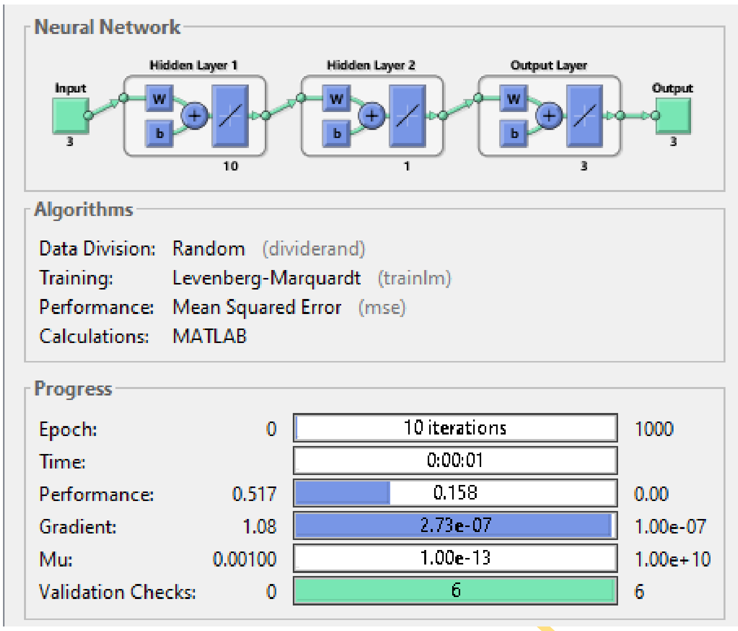

Figure 4.1. Adaptive calibration parametric results for Purelin – Purelin activation functions

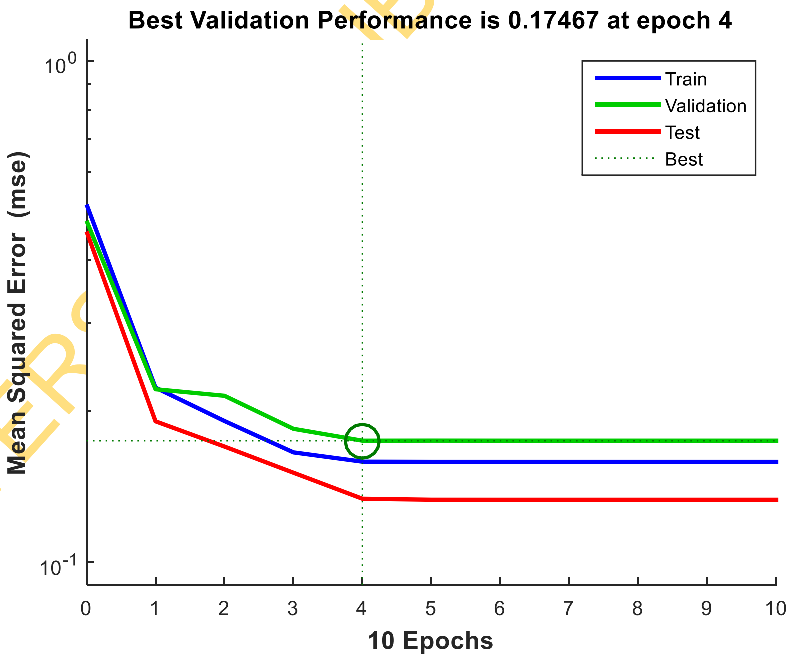

Figure 4.2. MSE results for Purelin – Purelin activation functions

The sum total of regression analysis result for Purelin – Purelin activation combination is 0.60694. The component parts of this regression are 0.60263 regression for training, 0.55185 regression for validation and 0.68284 regression for testing as shown in Figure 4.3.

4.2.1.2. Parametric results for hidden layer purelin activation function and output layer tansig activation function

In the second calibration, the activation function in the hidden layer is purelin but tansig is used for the output layer as shown in Figure 4.4. The calibration recorded total number of sixteen iterations in less than 1 second. The learning rate has a gradient descent of 7.41×10^{-8}. Six validation checks were also recorded during these iterations. Within the 16 epochs made, the calibration converges at the 10^{th} iteration and the mean squared error of 0.13862 was achieved as shown in Figure 4.5.

During purelin – tansig activation function-based calibration, the regression result for training is 0.66995, validation is 0.66924, testing is 0.69015. The overall regression analysis of 0.67271 was achieved as shown in Figure 4.6.

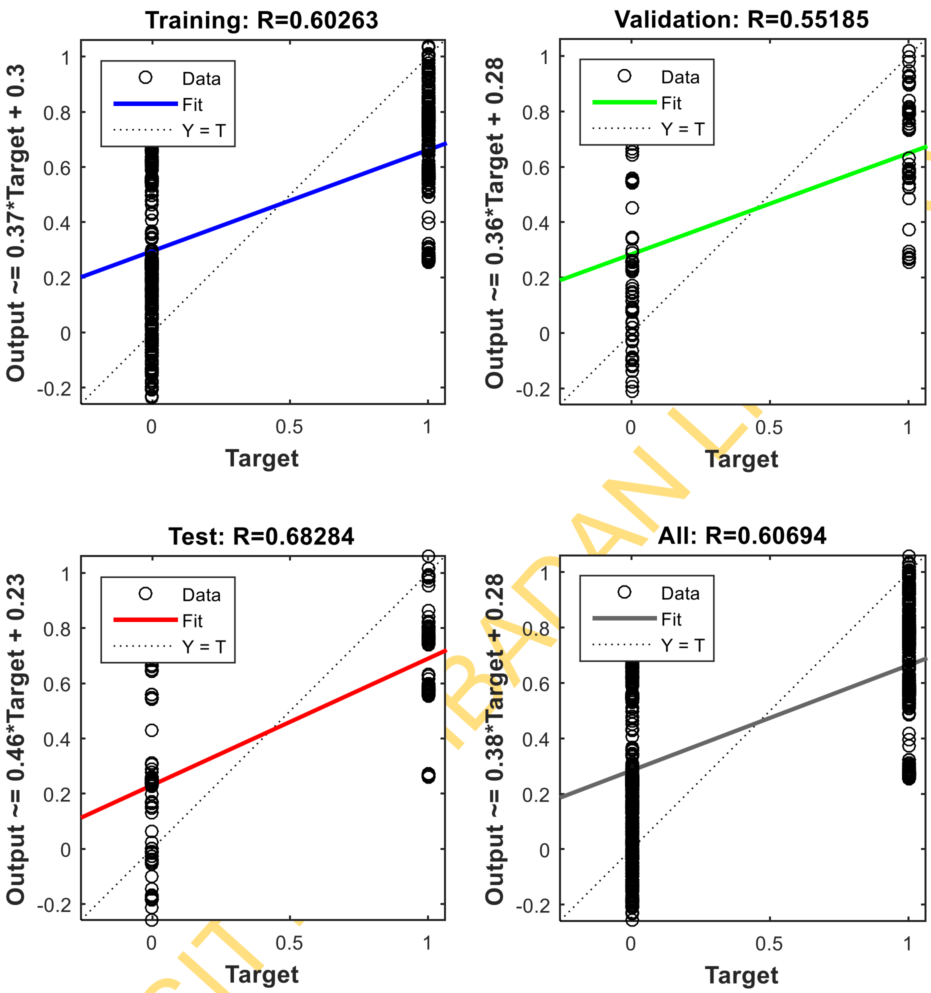

Figure 4.3. Regression results for Purelin – Purelin activation functions

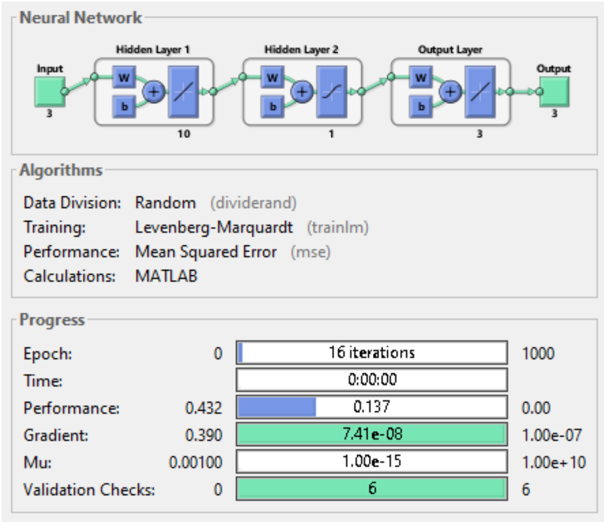

Figure 4.4. Adaptive calibration parametric results for Purelin – Tansig activation functions

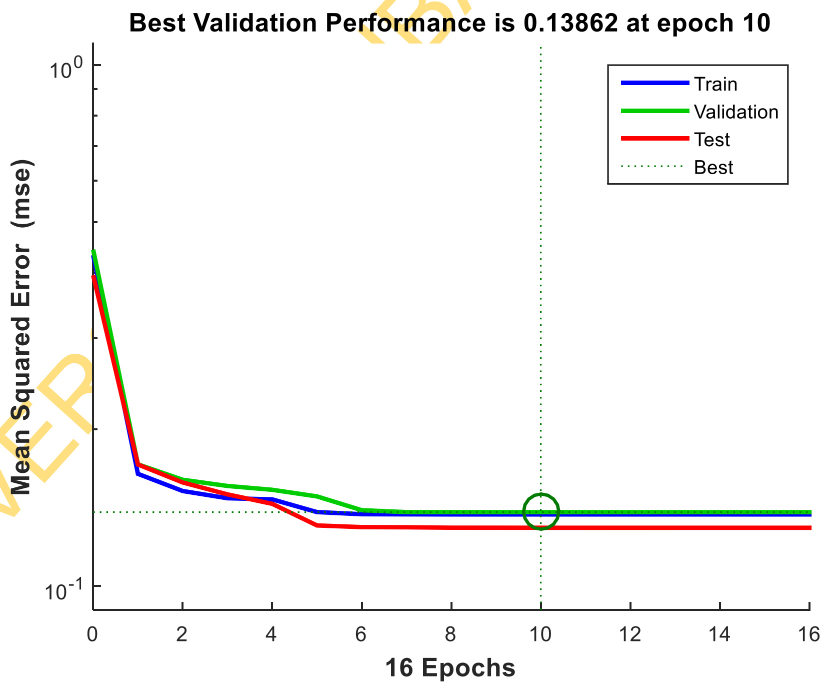

Figure 4.5. MSE results for Purelin – Tansig activation functions

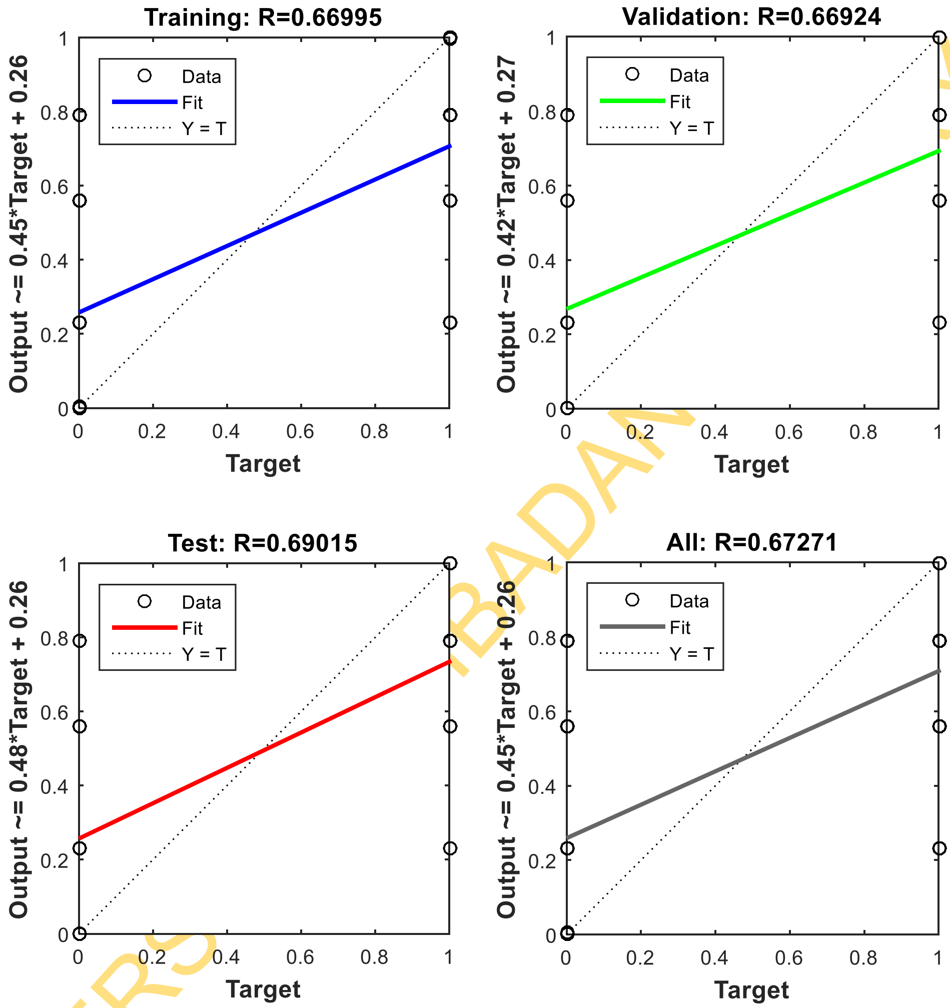

Figure 4.6. Regression results for Purelin – Tansig activation functions

4.2.1.3. Parametric results for hidden layer purelin activation function and output layer logsig activation function

In the combination of purelin – logsig activation functions in the hidden and output layer respectively, twelve iterations were made for the calibration in less than one second as shown in Figure 4.7. The gradient descent for the learning rate is 1.69×10^{-6}. The total of six validation checks were made during this calibration. The calibration converges at the 6th epoch with mean squared error of 0.15435 as shown in Figure 4.8.

The purelin – logsig pair achieved 0.6719 regression for training, 0.62127 regression for validation and 0.68375 regression for testing. The overall regression for this combination is 0.66579 as shown in Figure 4.9.

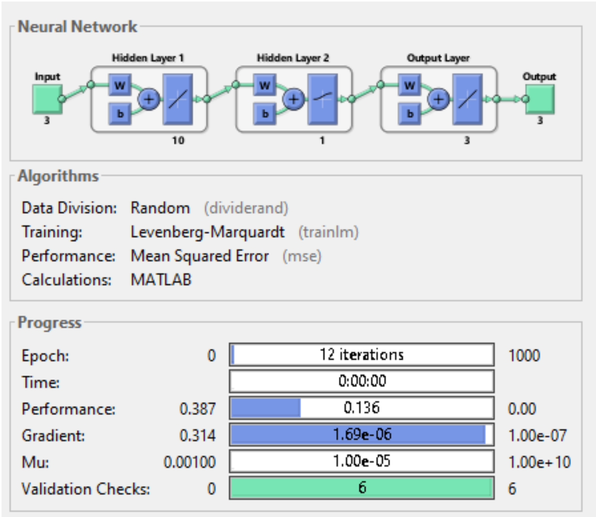

Figure 4.7. Adaptive calibration parametric results for Purelin – Logsig activation functions

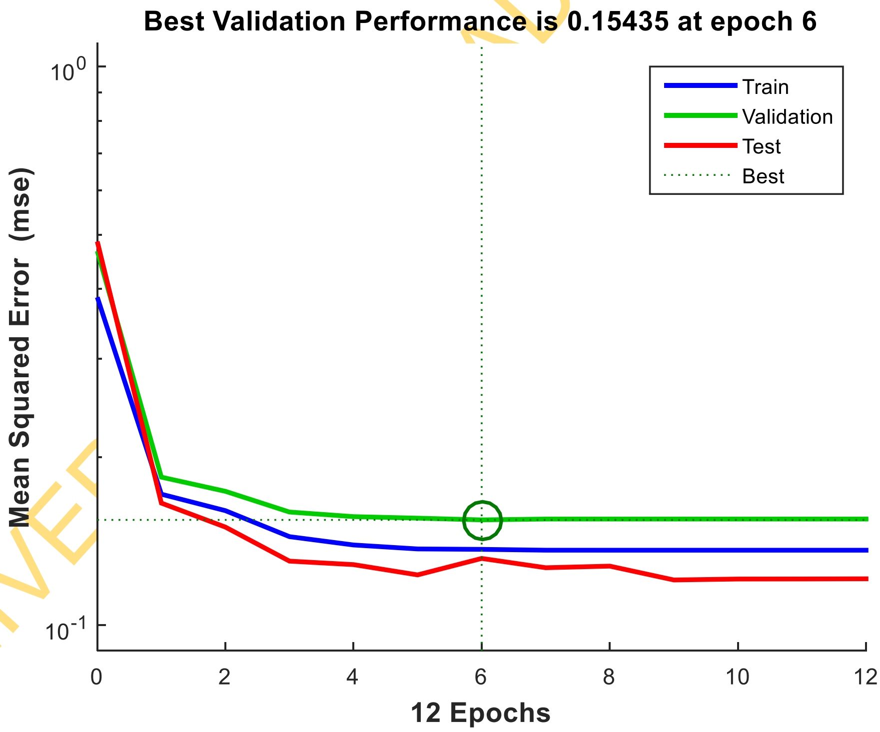

Figure 4.8. MSE results for Purelin – Logsig activation functions

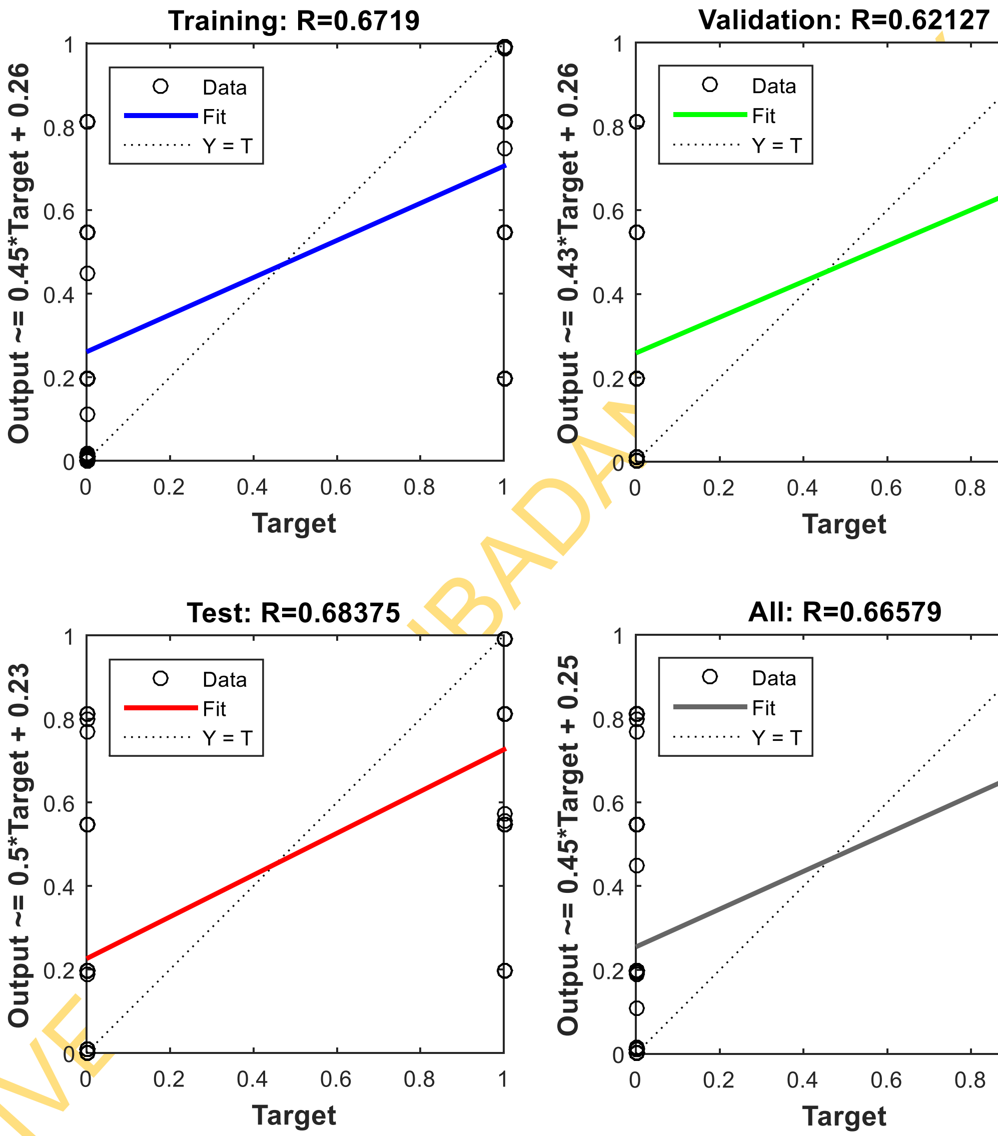

Figure 4.9. Regression results for Purelin – Logsig activation functions

4.2.1.4. Parametric results for hidden layer tansig activation function and output layer purelin activation function

The activation function pair of tansig – purelin attained total of 59 iterations with 5 validation checks. The rate of learning was done in the gradient descent of 9.23×10^{-8} as shown in Figure 4.10. The convergence of this pair was achieved at 54th epoch with MSE of 0.0037494 as in Figure 4.11.

The tansig – purelin achieved a training regression of 1. The validation regression for this activation combination attained 0.9925 and testing regression of 0.98378. The overall regression in the tansig – purelin combination is 0.99647 as shown in Figure 4.12.

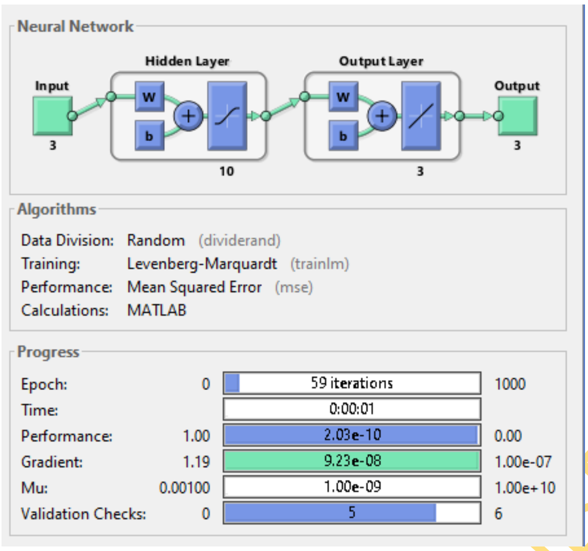

Figure 4.10. Adaptive calibration parametric results for Tansig – Purelin activation functions

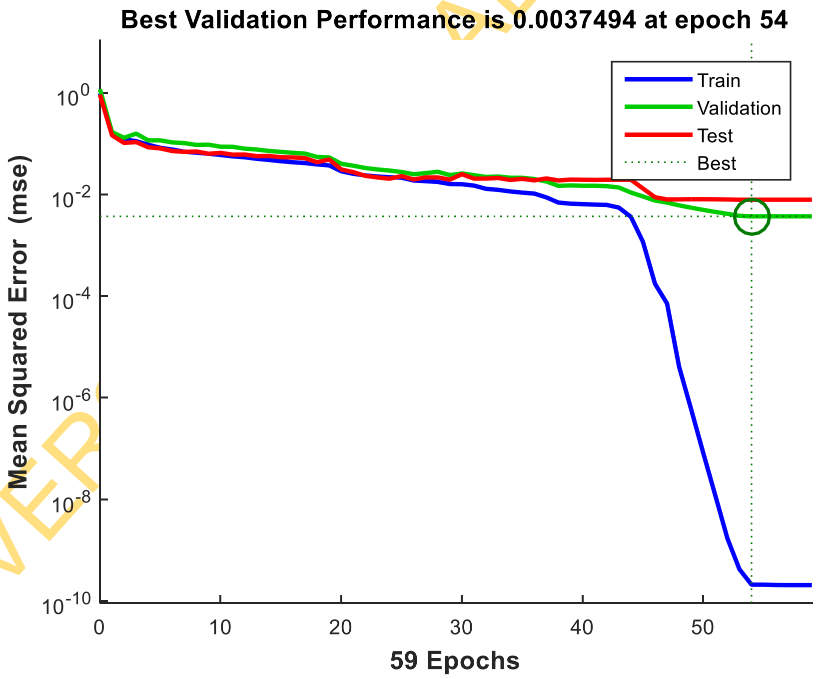

Figure 4.11. MSE results for Tansig – Purelin activation functions

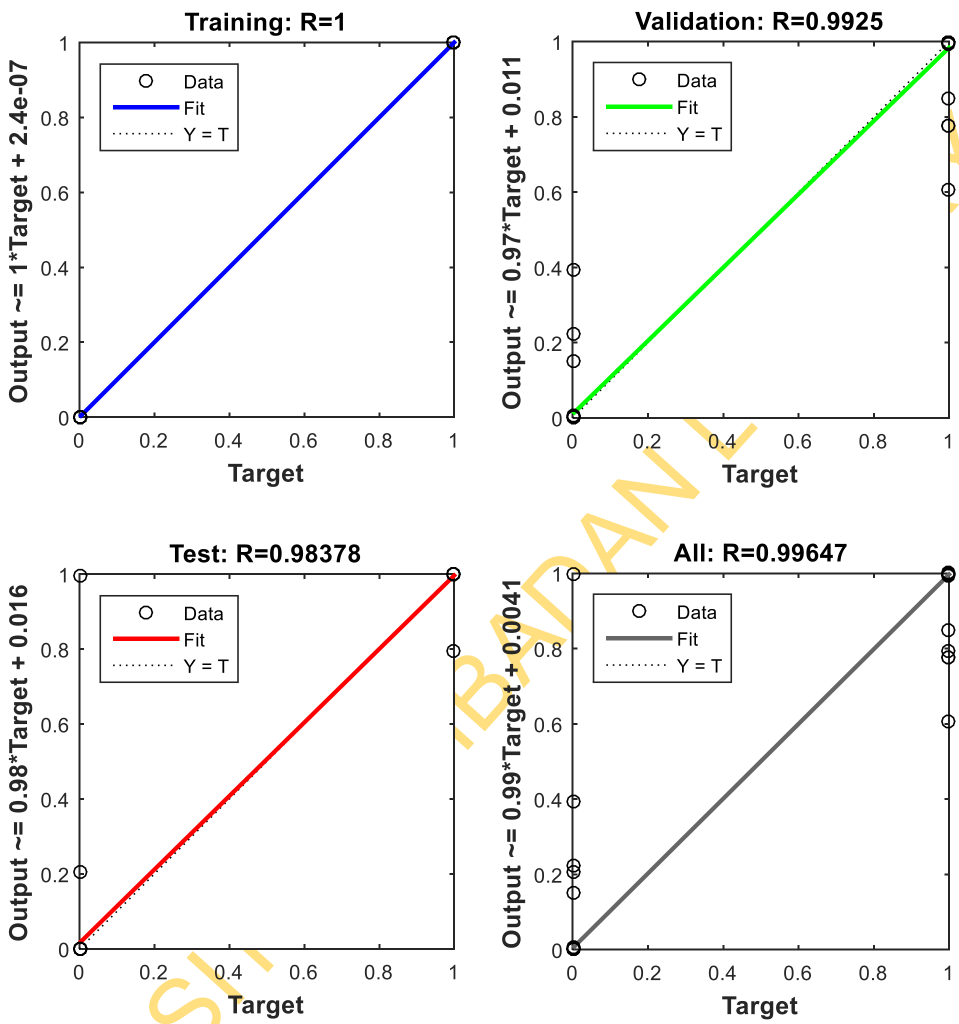

Figure 4.12. Regression results for Tansig – Purelin activation functions

4.2.1.5. Parametric results for hidden layer tansig activation function and output layer tansig activation function

The tansig – tansig activation function pair performed a total of 30 iterations with a gradient descent of 0.0136. The total validation checks of 6 were recorded as in Figure 4.13. The combination was converged at 24^{th} epoch and attained MSE of 0.11426 as shown in Figure 4.14.

The training regression for tansig – tansig activation function combination is 0.71276. The validation regression performed better with the value of 0.7373. The testing regression for this combination is 0.78202 as shown in Figure 4.15 with overall regression of 0.7269.

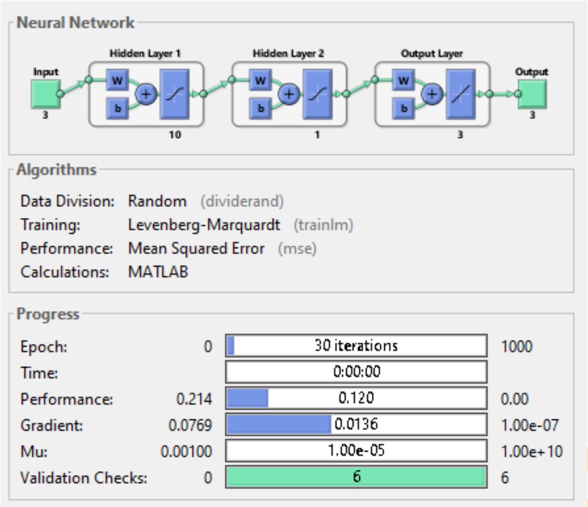

Figure 4.13. Adaptive calibration parametric results for Tansig – Tansig activation functions

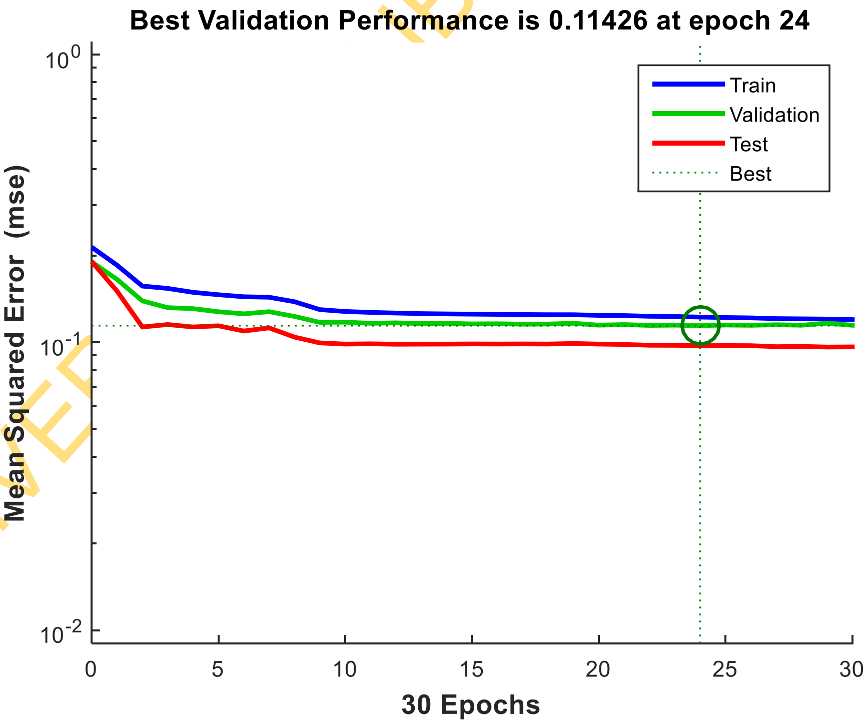

Figure 4.14. MSE results for Tansig – Tansig activation functions

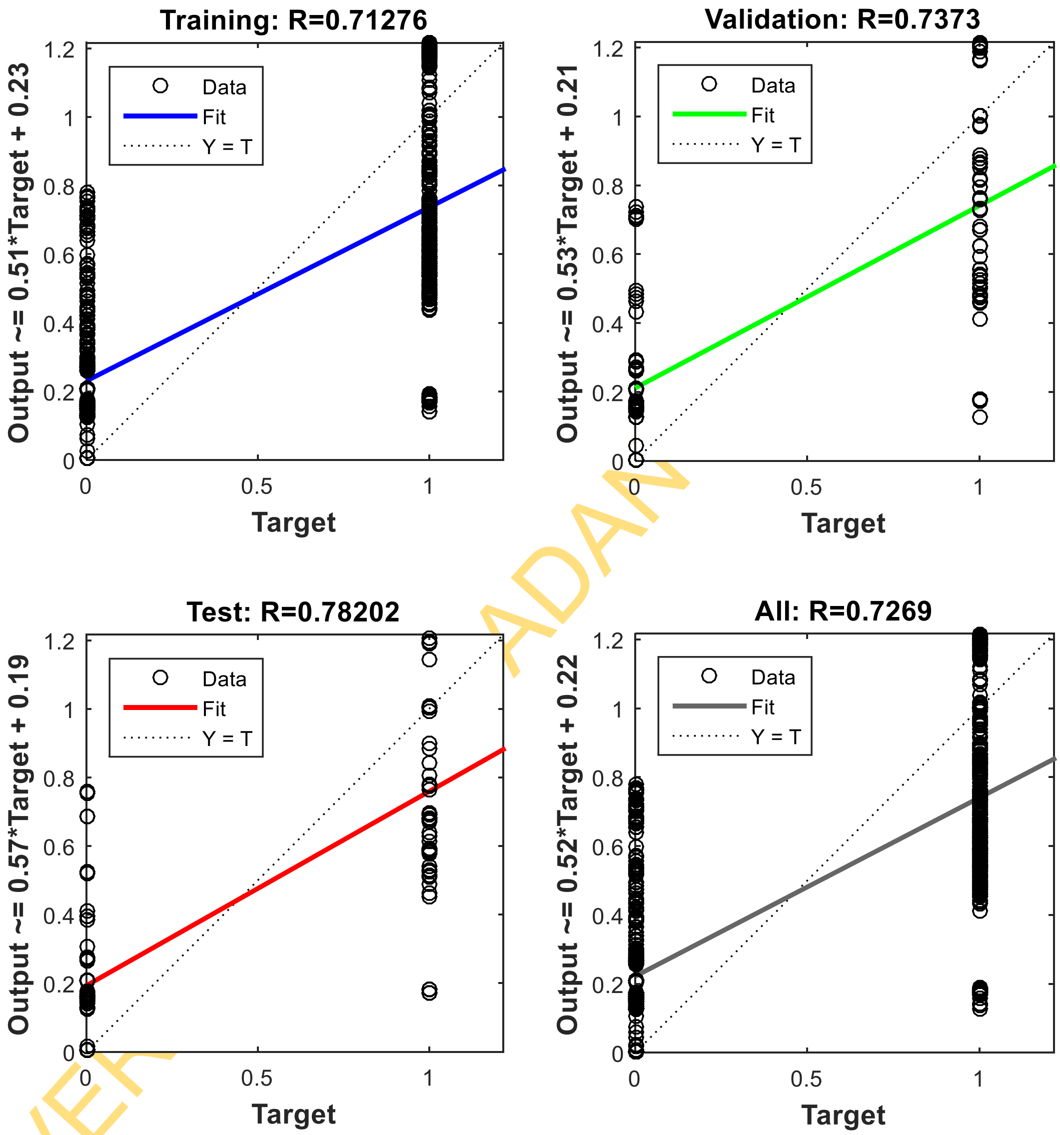

Figure 4.15. Regression results for Tansig – Tansig activation functions

4.2.1.6. Parametric results for hidden layer tansig activation function and output layer logsig activation function

The tansig – logsig activation function pair performed 71 iterations and recorded gradient descent of 4.4×10^{-6}, a total of 6 validation checks were carried out during these iterations as shown in Figure 4.16. This calibration pair achieved MSE of 0.14445 with convergence at 65th epoch as in Figure 4.17.

The tansig – logsig combination recorded training regression of 0.66394, validation regression of 0.64679 and testing regression of 0.73546. The overall regression is 0.67212 as shown in Figure 4.18.

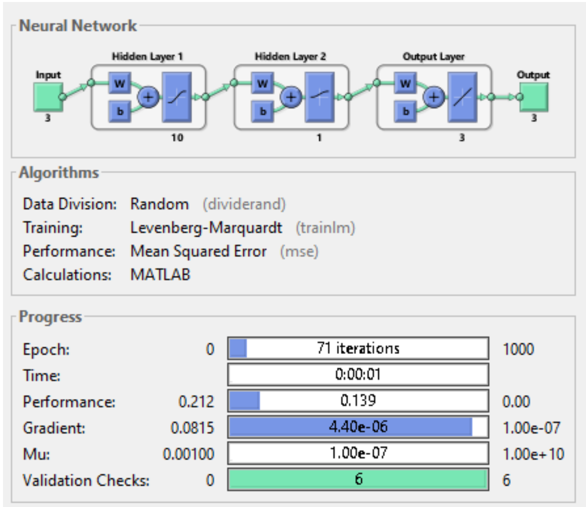

Figure 4.16. Adaptive calibration parametric results for Tansig – Logsig activation functions

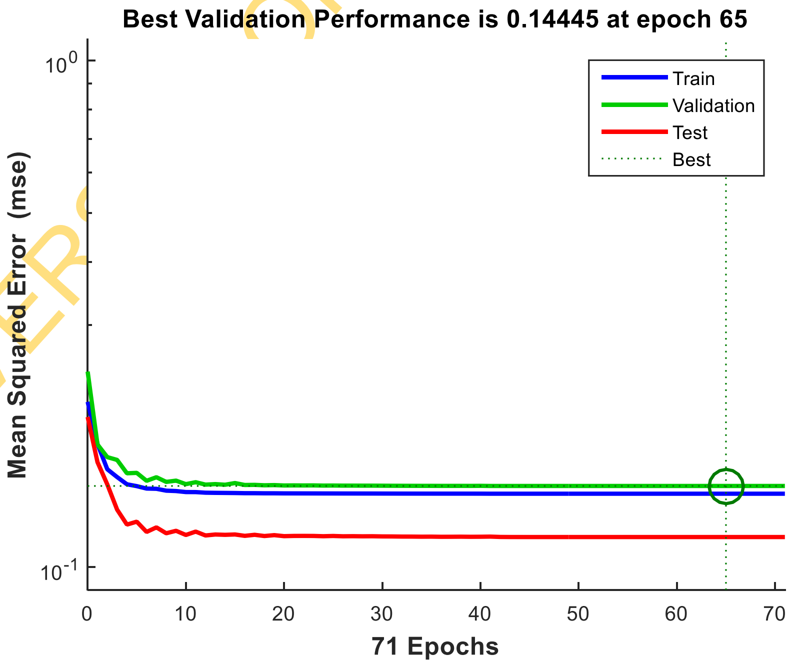

Figure 4.17. MSE results for Tansig – Logsig activation functions

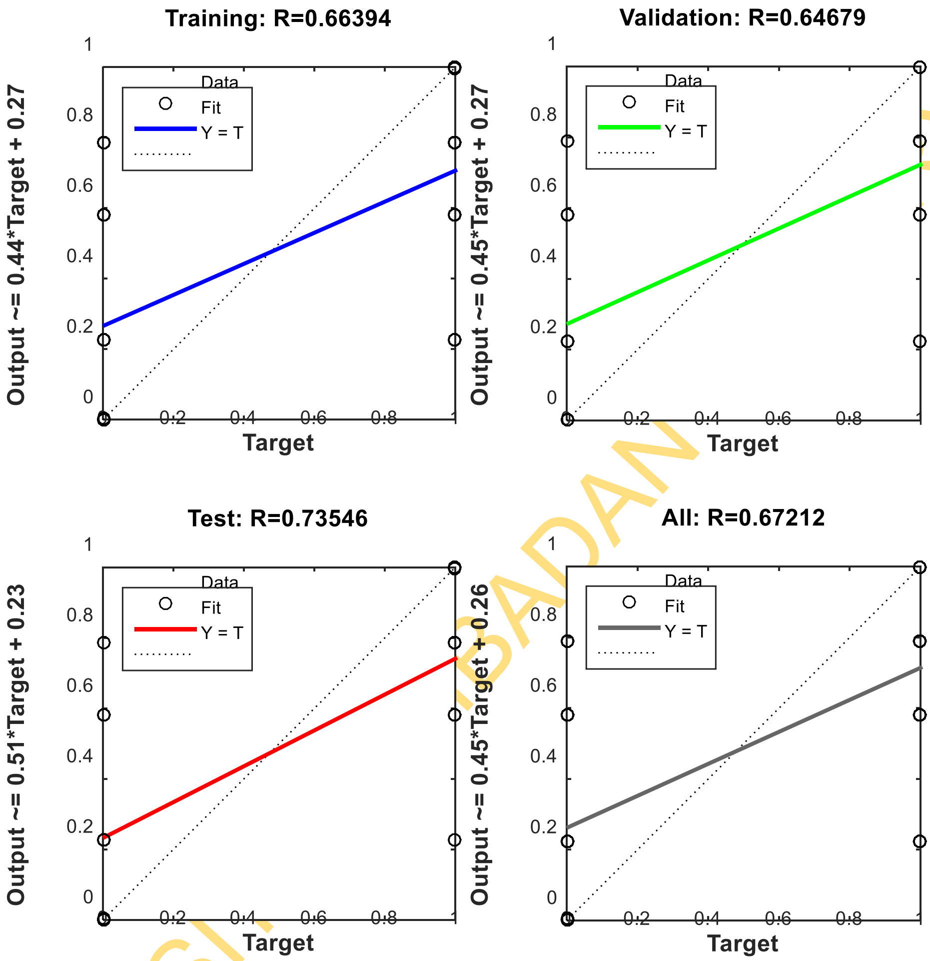

Figure 4.18. Regression results for Tansig – Logsig activation functions

4.2.1.7. Parametric results for hidden layer logsig activation function and output layer purelin activation function

The logsig – purelin activation combination performed 22 iterations within 3 seconds with gradient descent of 0.00483. A total of 6 validation checks were recorded as shown in Figure 4.19. The point of convergence was achieved at the 16^{th} epoch with MSE of 0.12116.

The logsig – purelin activation functions combination achieved the following regressions: 0.74987 for training, 0.71762 for validation, 0.43307 for testing. In Figure 4.21, the overall regression is 0.70023

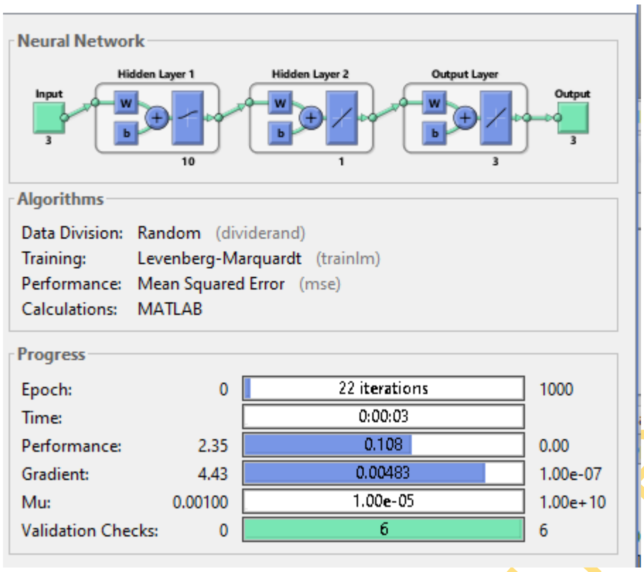

Figure 4.19. Adaptive calibration parametric results for Logsig – Purelin activation functions

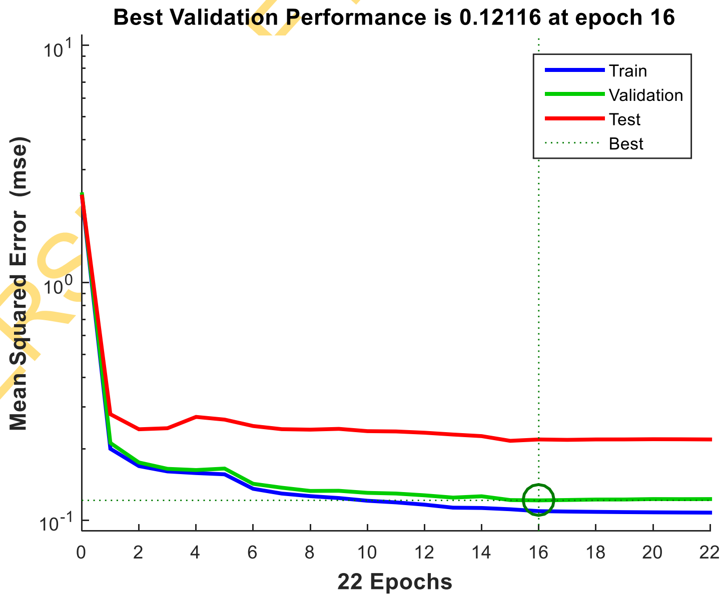

Figure 4.20. MSE results for Logsig – Purelin activation functions

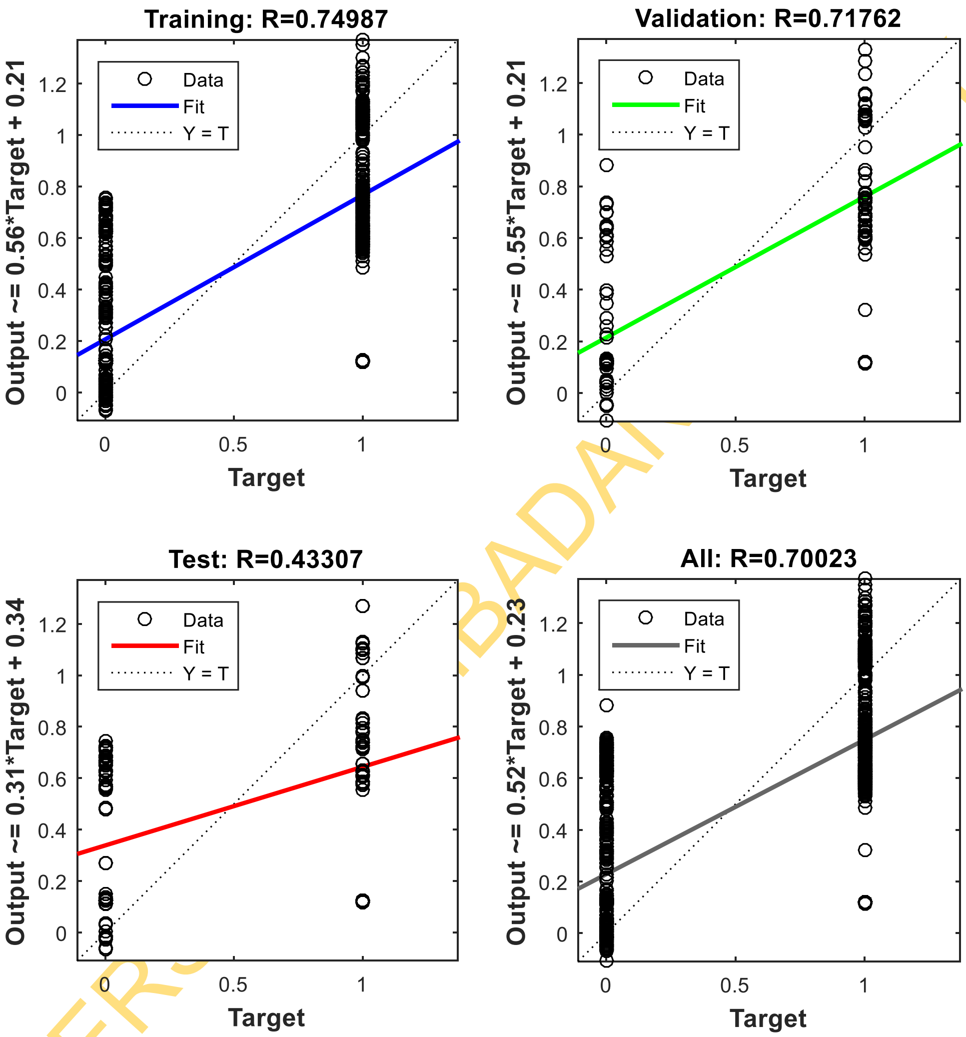

Figure 4.21. Regression results for Logsig – Purelin activation functions

4.2.1.8. Parametric results for hidden layer logsig activation function and output layer tansig activation function

In the logsig – tansig activation function pair, 20 iterations were made within 3 seconds. The gradient descent of 0.00384 was recorded with 6 validation checks as shown in Figure 4.22. With this combination, the MSE is 0.11431 at the 14th epoch convergence as clearly indicated in Figure 4.23.

At the 14th epoch convergence, the logsig – tansig combination achieved training regression of 0.70723, validation regression of 0.74044 and testing regression 0.70042. The overall regression of 0.71093 was attained as in Figure 4.24.

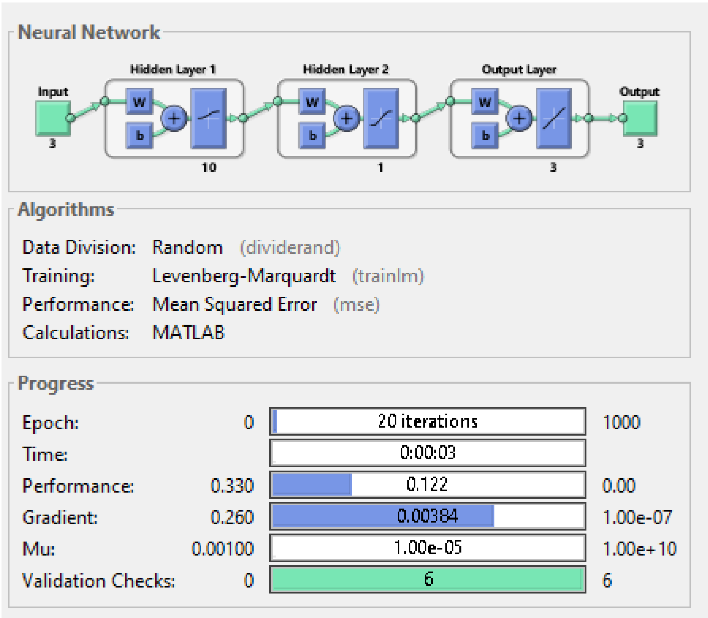

Figure 4.22. Adaptive calibration parametric results for Logsig – Tansig activation functions

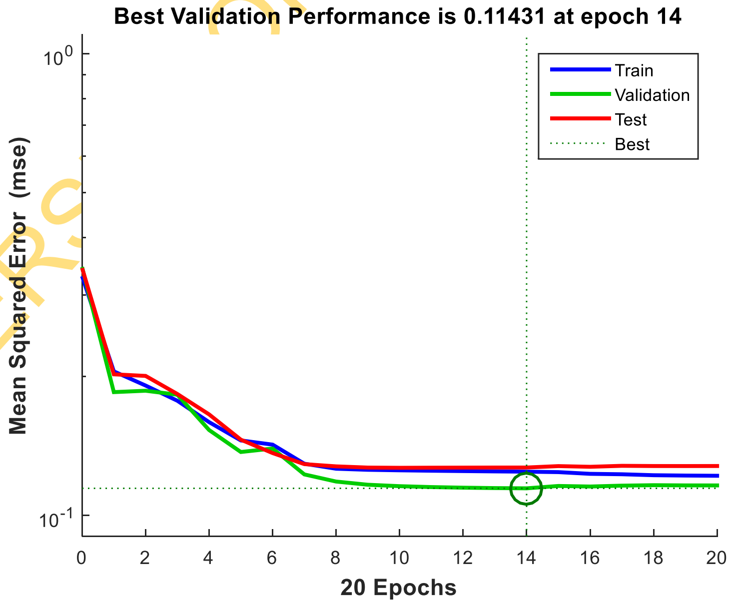

Figure 4.23. MSE results for Logsig – Tansig activation functions

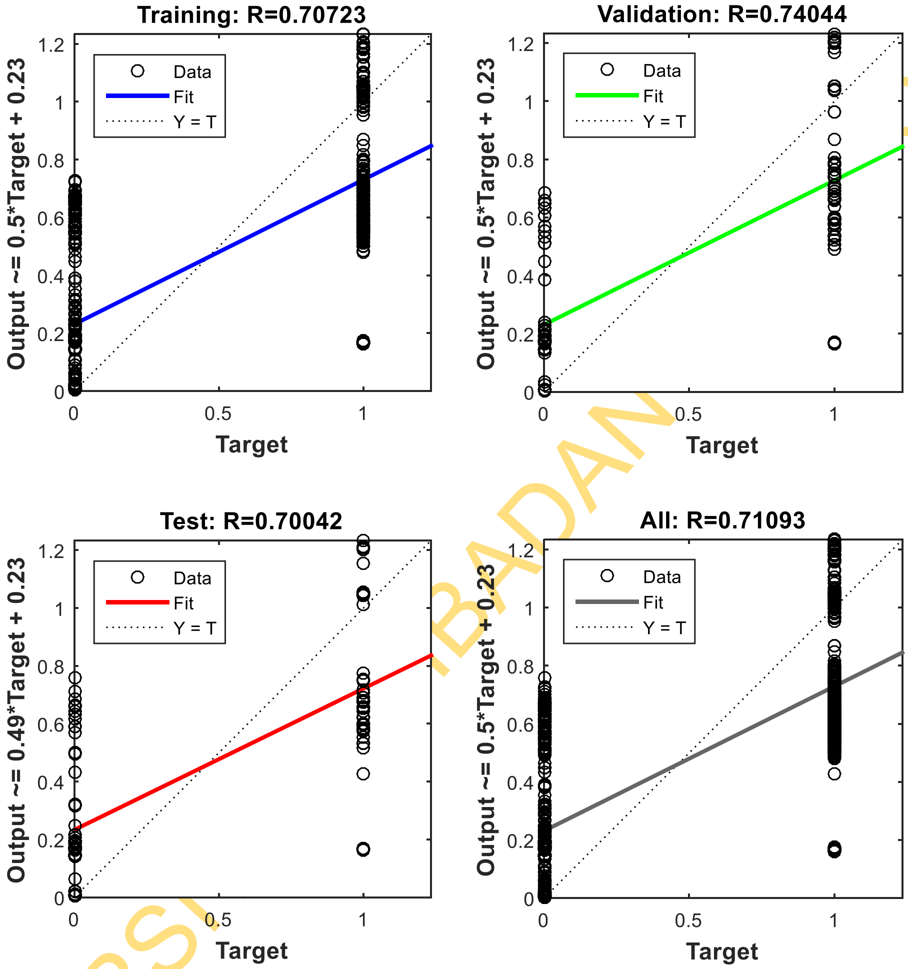

Figure 4.24. Regression results for Logsig – Tansig activation functions

4.2.1.9. Parametric results for hidden layer logsig activation function and output layer logsig activation function

In Figure 4.25, the logsig – logsig, 18 iterations were recorded within 3 seconds. Gradient descent of 0.00117 was achieved with 6 validation checks. The activation function reached convergence point at the 12^{th} epoch with MSE of 0.1427 as in Figure 4.26.

The training regression of 0.72164 was attained with validation regression of 0.6579 as shown in Figure 4.27. From the same figure, testing regression of 0.6626 was recorded and the overall regression of 0.70269 was achieved.

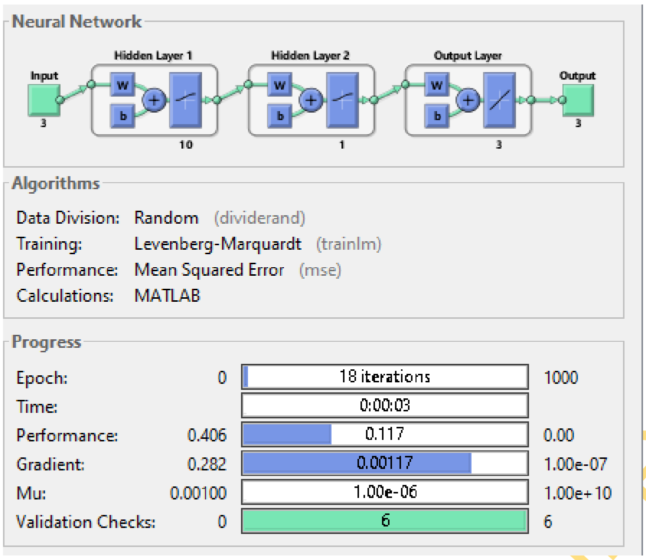

Figure 4.25. Adaptive calibration parametric results for Logsig – Logsig activation functions

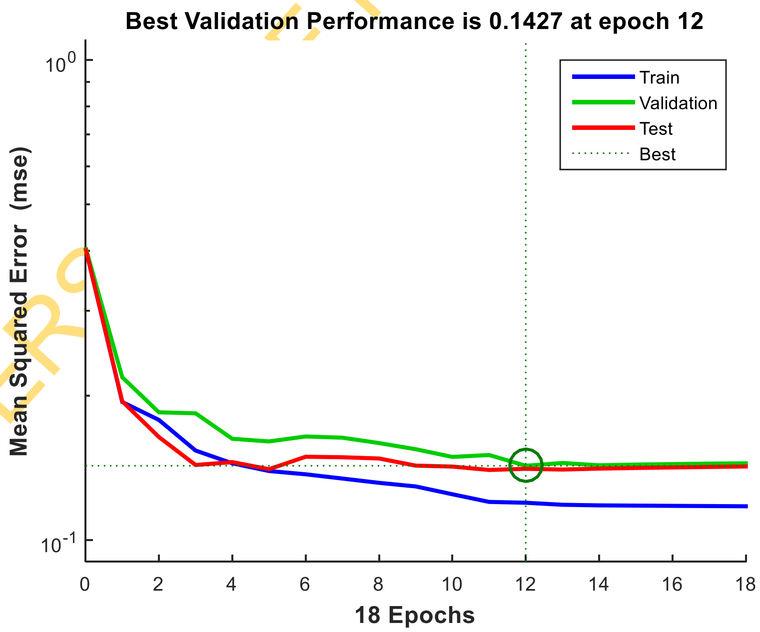

Figure 4.26. MSE results for Logsig – Logsig activation functions

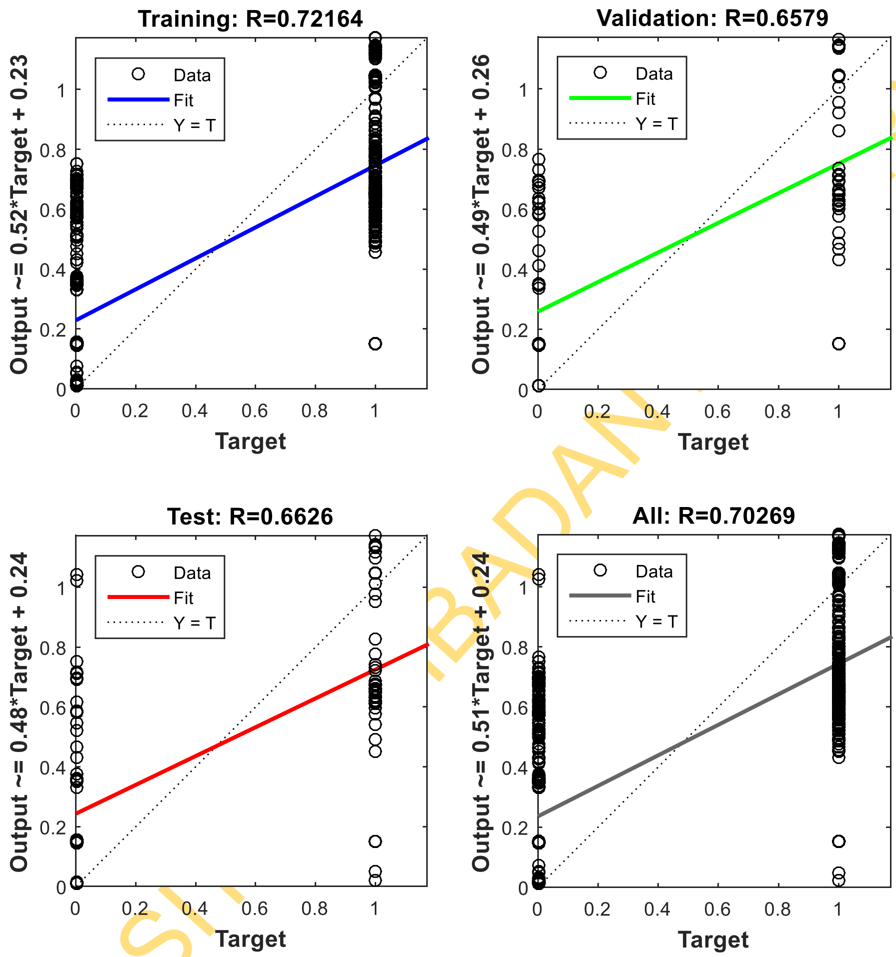

Figure 4.27. Regression results for Logsig – Logsig activation functions

4.2.2. Dynamically Adaptive Vision Calibrator for Vision Impaired Users

From the developed ANN-based model, the model coefficients in equation (3.36) is computed as the product of input weight matrix and layer weight matrix. The coefficients are given in equation (4.1),

$$\begin{bmatrix} a_1 & b_1 & c_1 \\ a_2 & b_2 & c_2 \\ a_3 & b_3 & c_3 \end{bmatrix} = \begin{bmatrix} -597.0703 & 463.6073 & 573.8042 \\ -1.7474 & 1.9383 & 0.4508 \\ 8.4985 & -1.2436 & -17.1718 \end{bmatrix} \tag{4.1}$$

Therefore, in equations (3.12), (3.32), (3.33) and (3.34), the ANN-based optimised mathematical model of the developed dynamic thresholding model is given in equation (4.2),

$$\left.\begin{aligned} OP1 &= 463.6073Ps - 597.0703Va + 573.8042Rr \\ OP2 &= 1.9383Ps - 1.7474Va + 0.4508Rr \\ OP3 &= 8.4985Va - 1.2436Ps - 17.1718Rr \end{aligned}\right\} \tag{4.2}$$

4.2.3. Dynamic Thresholding Values

In order to get best performance of the intelligent model, dynamic thresholding algorithm was developed to get the best threshold value using training dataset as seen in Table 4.4. The best three accuracy values were received the following threshold values: 0.5, 0.505 and 0.58. The result of error computation and intelligent adjustment during model training is presented in Appendix B.

Table 4.4. Dynamic thresholding for training dataset

Threshold	Accuracy						Average Accuracy	Standard Deviation
0.4	97.42857143	94.2857143	99.57143	99.85714	98.71429	97.97143	97.97142857	2.266436563
0.405	97.42857143	96.5714286	97.71429	98.28571	99.28571	97.85714	97.85714286	1.010152545
0.41	98.85714286	97.4285714	99.85714	99.57143	99.57143	99.05714	99.05714286	0.982499935
0.415	98.85714286	98.7142857	98.42857	99.42857	99	98.88571	98.88571429	0.369776546
0.42	99.28571429	97.1428571	99.14286	99.28571	99.71429	98.91429	98.91428571	1.01317847
0.425	100	94.8571429	98	98.85714	99.14286	98.17143	98.17142857	1.985662898
0.43	94.57142857	99.7142857	99.14286	98.14286	99	98.11429	98.11428571	2.058828674
0.435	99.28571429	99.2857143	98.28571	99.28571	99.42857	99.11429	99.11428571	0.467297921
0.44	98.85714286	98.4285714	99.57143	99.14286	95.57143	98.31429	98.31428571	1.58886431
0.445	95.14285714	95.8571429	97.57143	97.42857	98.28571	96.85714	96.85714286	1.305404777
0.45	99.85714286	99.1428571	99	98.28571	99.42857	99.14286	99.14285714	0.580288457
0.455	99.57142857	98.4285714	99	100	99.28571	99.25714	99.25714286	0.592469753
0.46	100	98.8571429	99.14286	98	98.71429	98.94286	98.94285714	0.725624291
0.465	99.85714286	98.4285714	98.42857	99.85714	99.28571	99.17143	99.17142857	0.717137166
0.47	100	99.8571429	97.57143	99.28571	100	99.34286	99.34285714	1.033124842
0.475	99.28571429	99.8571429	99.71429	99.57143	98	99.28571	99.28571429	0.749149177
0.48	99.28571429	99	99.28571	99.42857	98.85714	99.17143	99.17142857	0.234738239
0.485	99	96	99.14286	98.85714	95.85714	97.77143	97.77142857	1.686077443
0.49	99.85714286	99.2857143	99.71429	98.28571	98.42857	99.11429	99.11428571	0.724216677
0.495	98.85714286	99.2857143	99.57143	99.28571	98.71429	99.14286	99.14285714	0.349927106
0.5	**99.71428571**	**99.7142857**	**99.42857**	**99.71429**	**99.42857**	**99.6**	**99.6**	**0.156492159**
0.505	**99.85714286**	**99.4285714**	**98.85714**	**99.71429**	**99.28571**	**99.42857**	**99.42857143**	**0.391230398**
0.51	99	97.4285714	99.71429	99.57143	99.57143	99.05714	99.05714286	0.950832074
0.515	99.28571429	99.2857143	99.57143	98.57143	99.14286	99.17143	99.17142857	0.369776546
0.52	99.71428571	96.2857143	99.71429	99.71429	99.85714	99.05714	99.05714286	1.55051012
0.525	98.42857143	98.1428571	98.71429	99.85714	99.42857	98.91429	98.91428571	0.711422834
0.53	97.85714286	99.5714286	99.71429	99.42857	99.57143	99.22857	99.22857143	0.773278206
0.535	99.57142857	96.5714286	99.85714	98.71429	95.85714	98.11429	98.11428571	1.802492605
0.54	99.57142857	96.2857143	98.85714	99.57143	97.85714	98.42857	98.42857143	1.38873015
0.545	96.71428571	99.1428571	98	100	98.14286	98.4	98.4	1.242939242
0.55	99.14285714	99.8571429	98.14286	99.28571	99.71429	99.22857	99.22857143	0.674612512
0.555	98.14285714	99.7142857	99.85714	97.71429	96.14286	98.31429	98.31428571	1.536627635
0.56	96.42857143	99	99.85714	99.71429	99.85714	98.97143	98.97142857	1.465243589
0.565	98.42857143	96.8571429	99.42857	99.57143	99.42857	98.74286	98.74285714	1.149090146
0.57	95.57142857	98	99	97.28571	95.28571	97.02857	97.02857143	1.585649934
0.575	99	99.1428571	99.71429	98.42857	97.42857	98.74286	98.74285714	0.86543607
0.58	**99.42857143**	**99.2857143**	**99.85714**	**98.85714**	**99.71429**	**99.42857**	**99.42857143**	**0.391230398**
0.585	99	99.8571429	99.71429	95.28571	99.85714	98.74286	98.74285714	1.96499987
0.59	99.85714286	97.2857143	98.85714	99.28571	98.28571	98.71429	98.71428571	0.984574911
0.595	95	99.1428571	99.85714	99.14286	99.71429	98.57143	98.57142857	2.022828894
0.6	99.28571429	94.8571429	96.14286	98.85714	93.57143	96.54286	96.54285714	2.485467968

From the performance of the new model, there are several maximal values of accuracy as seen in Figure 4.28. But the global maximal is at 0.5 threshold value.

The consistency of the performance of the threshold value (0.5) is also seen in Figure 4.29 by having the least standard deviation.

The threshold value of 0.5 which gave best performance with the training dataset was chosen and used for testing dataset. To further validate its performance, the best three thresholds were used on the testing dataset. Clearly, among the three thresholds, 0.5 threshold value gives the highest accuracy of magnification computation of 97.51 accuracy as seen in Table 4.5.

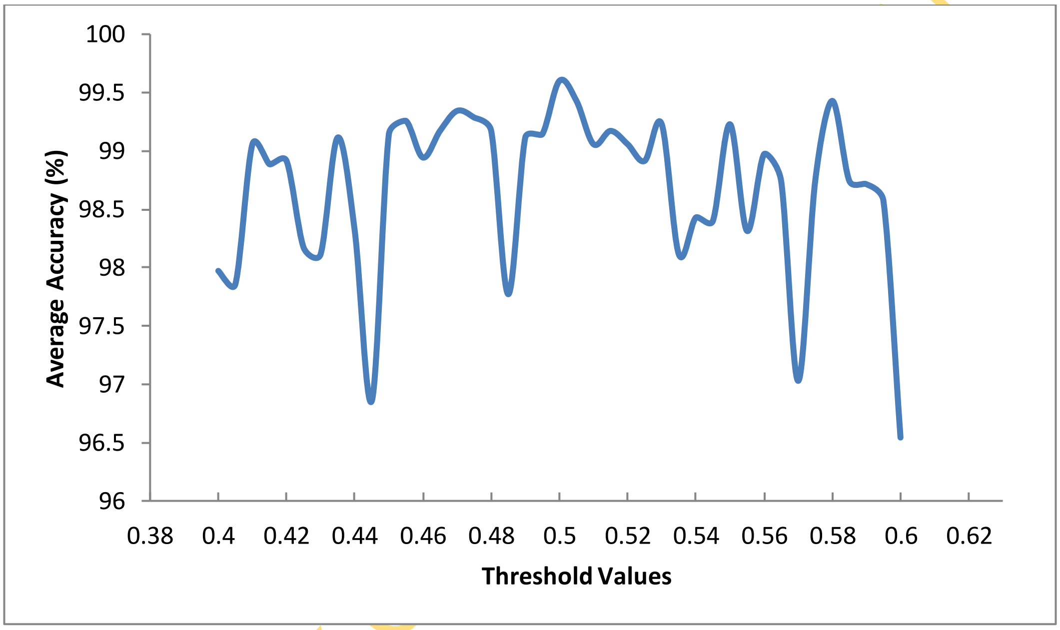

Figure 4.28. Average accuracy versus threshold values

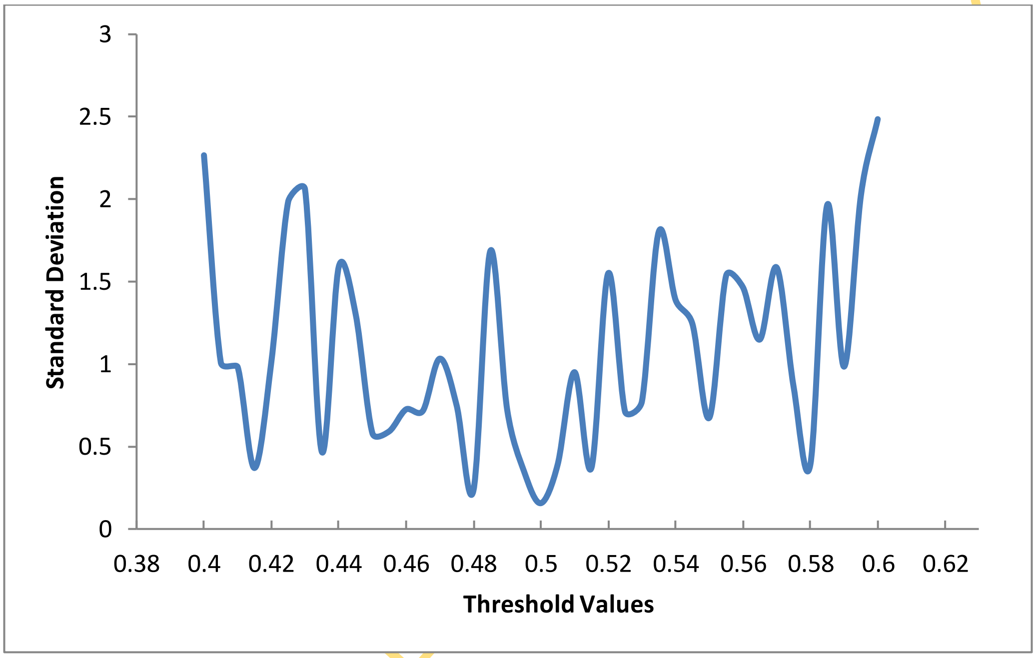

Figure 4.29. Standard deviation versus threshold values

Table 4.5. Thresholding for testing dataset

Threshold	Accuracy						Average Accuracy	Standard Deviatiion
0.5	**99.6678**	**95.0166**	**99.3355**	**97.01**	**96.6777**	**97.3422**	**97.5083**	**1.590411762**
0.505	97.3422	93.0233	98.6711	98.6711	94.3522	98.0066	96.67775	2.195351611
0.58	94.0199	95.0166	92.0266	97.01	99.3355	94.6844	95.34883333	2.309694589

4.2.4. Implementation and evaluation of Dynamic Thresholding Algorithm (DTA)

The series of activation function combinations in the hidden and output layers are shown and evaluated from Figure 4.30 to Figure 4.47. The Mean Absolute Errors (MAEs) were computed based on MSE and Root Mean Squared Error (RMSE) of each combination. The best performance is achieved in the parametric activation function combination of *Tansig-Purelin* in Figure 4.36 and Figure 4.37.

4.2.4.1. MAEs for Purelin-Purelin Activation Functions Combination

With purelin – purelin combination, the MAE based on MSE of the input parameter calibration is shown in Figure 4.30. Lower MAE was recorded from the first 100 Vision Impaired Users (VIUs) while higher values of MAE were observed from 250th to 300th VIU. The MAE based on RMSE also showed the same trend as clearly indicated in Figure 4.31. The results of parametric error and MAE of calibration for purelin-purelin combination is shown in Appendix C.

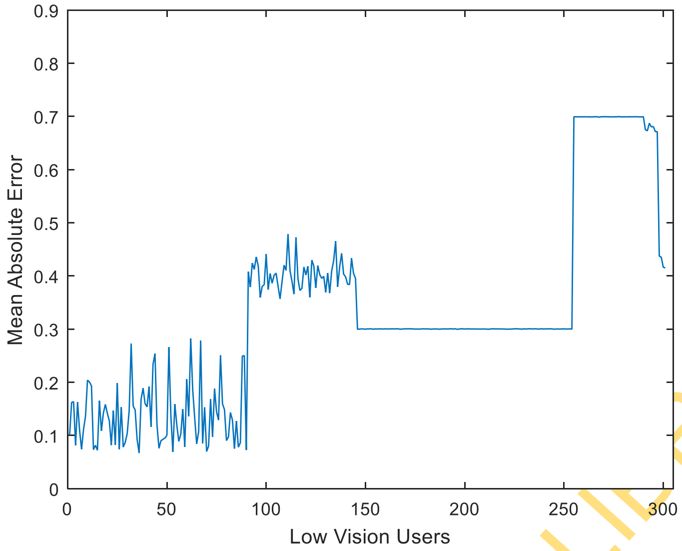

Figure 4.30. MAE for Purelin-Purelin Activation Functions Combination based on MSE

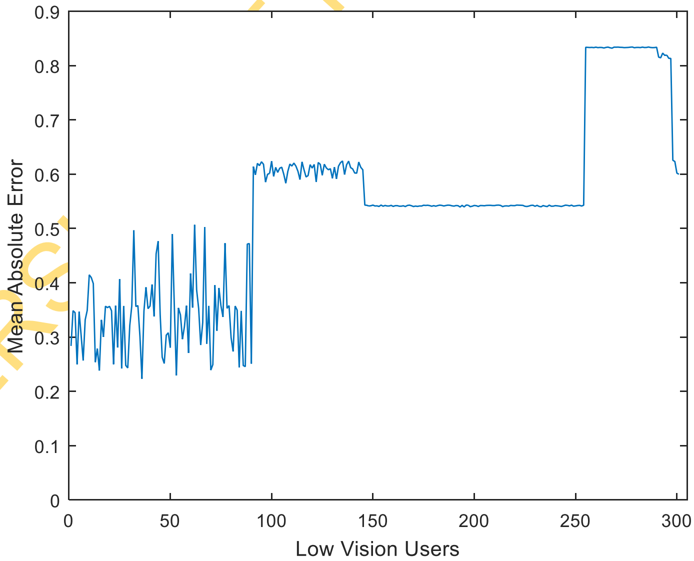

Figure 4.31. MAE for Purelin-Purelin Activation Functions Combination based on RMSE

4.2.4.2. MAEs for Purelin-Tansig Activation Function Combination

The MAE based on MSE for purelin – tansig activation function combination achieved least values (best performance) from the first 90 VIUs while highest MAE (lowest performance) was 250th to 290th VIU as shown in Figure 4.32. The purelin-tansig combination achieved a better performance than purelin-purelin pair. In Figure 4.33, MAE based on RMSE for purelin-tansig shows a consistent result with MAE based on MSE. The corresponding error in the parametric calibration with the MAE is shown in Appendix D.

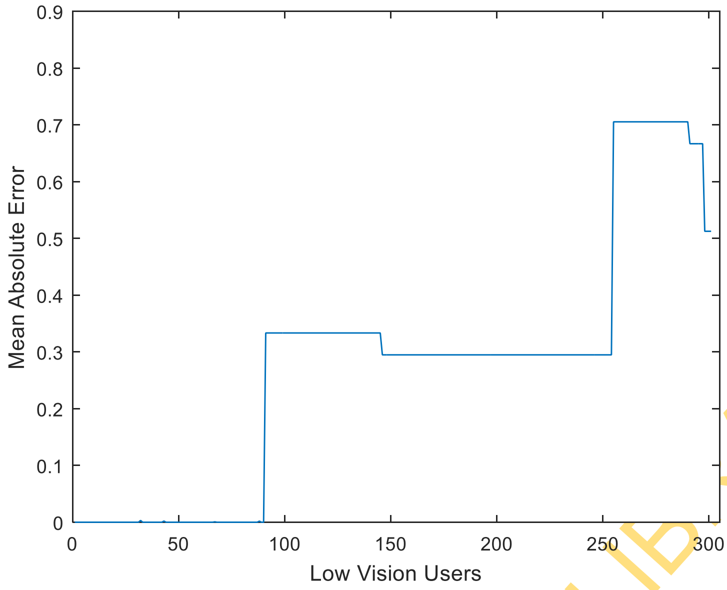

Figure 4.32. MAE for Purelin-Tansig Activation Function Combination based on MSE

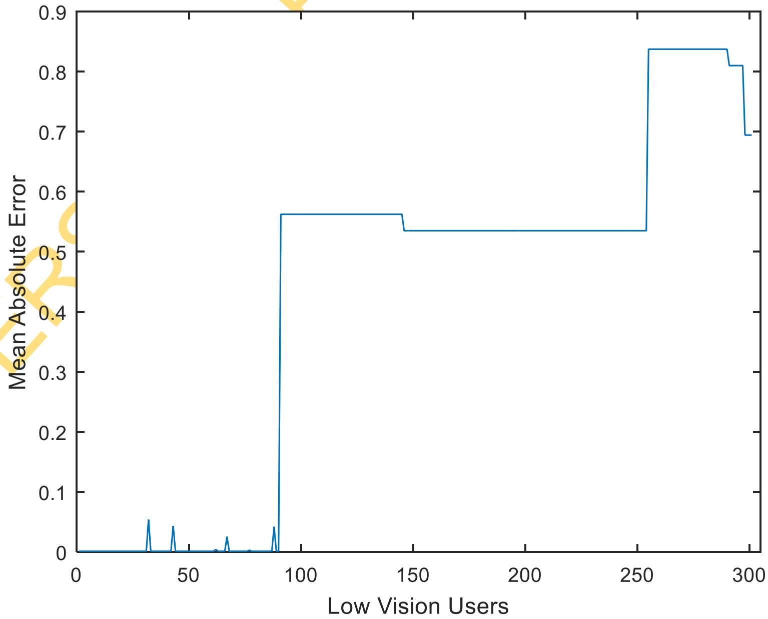

Figure 4.33. MAE for Purelin-Tansig Activation Function Combination based on RMSE

4.2.4.3. MAEs for Purelin-Logsig Activation Function Combination

The MAE based on MSE for purelin-logsig recorded least values from 1^{st} to 90^{th} VIU while highest values were observed from 250^{th} to 290^{th} VIU as shown in Figure 4.34. However, this activation function pair could not properly handle some outlier data within the first 90 VIUs. As shown in Figure 4.35, MAE based on RMSE generally shows a consistent results with MAE based on MSE. It however reveals more pronounced outlier data within the first 90 VIUs. The error in calibrating the user's parameters with associated MAE is presented in Appendix E.

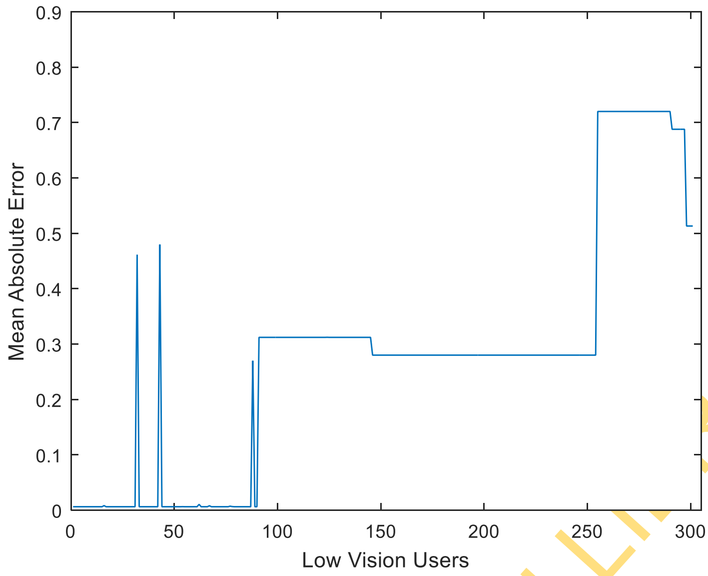

Figure 4.34. MAE for Purelin-Logsig Activation Function Combination based on MSE

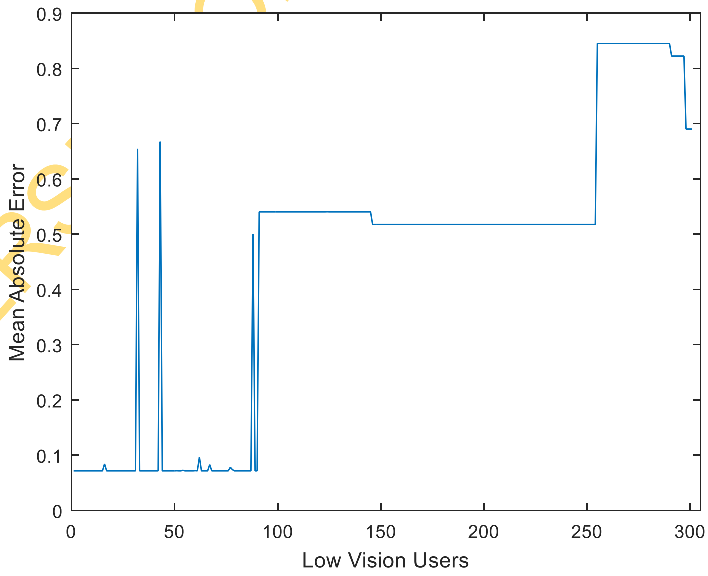

Figure 4.35. MAE for Purelin-Logsig Activation Function Combination based on RMSE

4.2.4.4. MAEs for Tansig-Purelin Activation Function Combination

The MAE based on MSE for tansig-purelin activation combination achieved best performance over all other activation function combinations by achieving general values very close to zero from the 1st VIU to the last VIU as shown in Figure 4.36. There are however 5 outliers within the calibration data. In Figure 4.37, MAE based on RMSE shows similar trends to the MAE based on MSE. The outliers are more pronounced with additional 2 insignificant outliers. The parametric calibration error with corresponding MAE is presented in Appendix F.

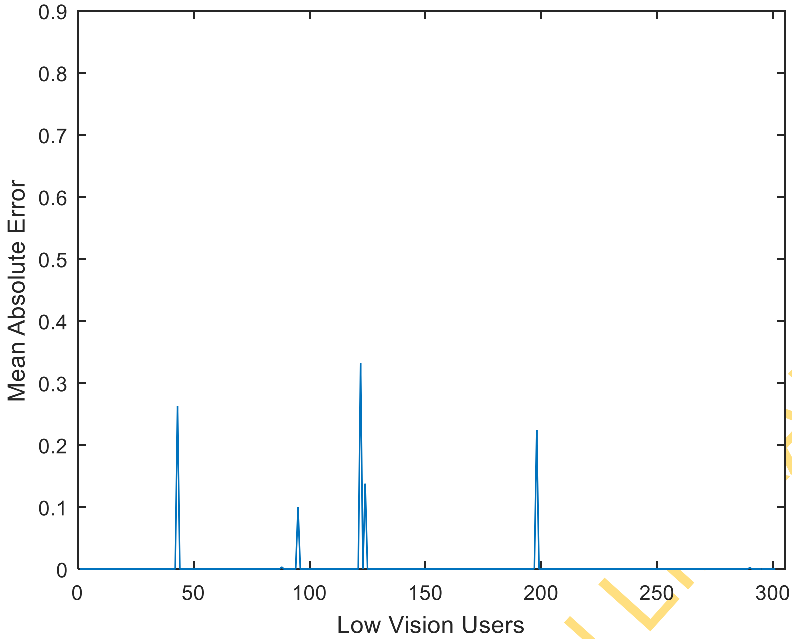

Figure 4.36. MAE for Tansig-Purelin Activation Function Combination based on MSE

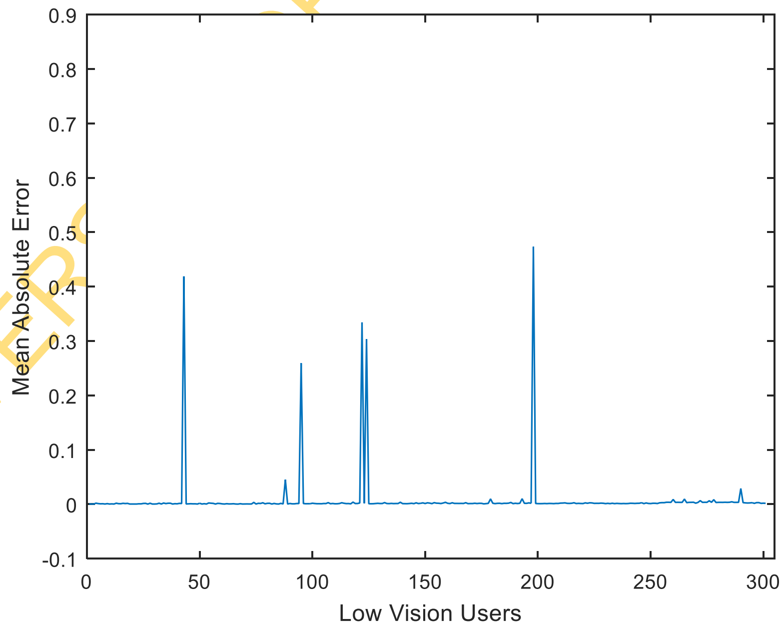

Figure 4.37. MAE for Tansig-Purelin Activation Function Combination based on RMSE

4.2.4.5. MAEs for Tansig-Tansig Activation Function Combination

The values of MAE based on MSE for tansig-tansig combination were least within the first 90 VIUs with gradual declining performance towards the last VIU as shown in Figure 4.38. Similar trend was recorded by the MAE based on RMSE as clearly indicated in Figure 4.39. The error in user's parameter calibration along with MAE is in Appendix G.

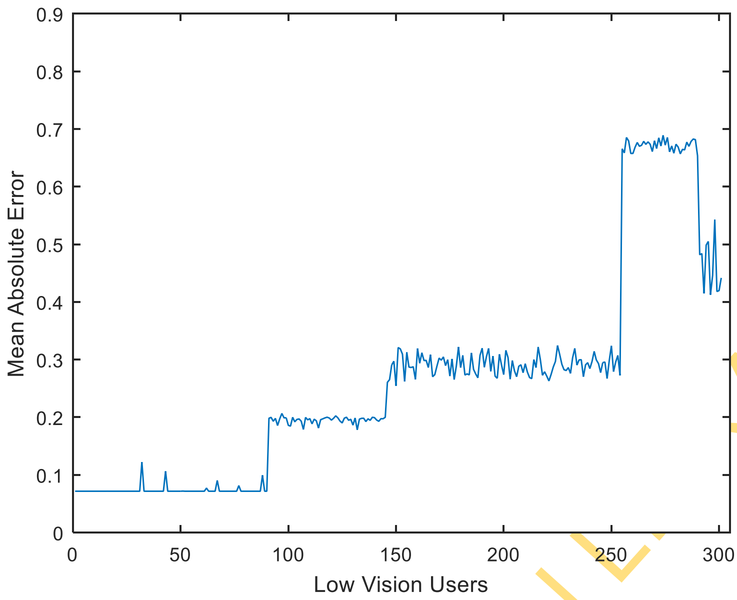

Figure 4.38. MAE for Tansig-Tansig Activation Function Combination based on MSE

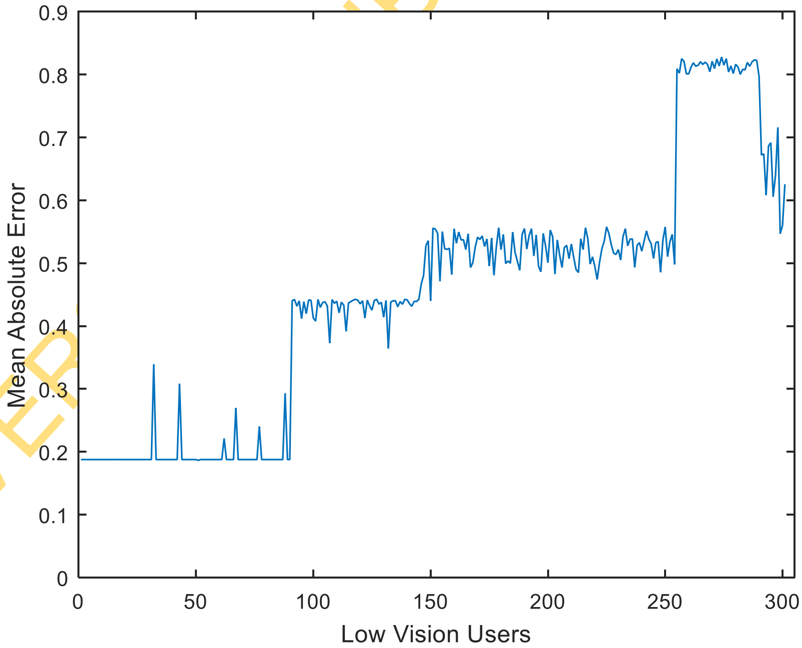

Figure 4.39. MAE for Tansig-Tansig Activation Function Combination based on RMSE

4.2.4.6. MAEs for Tansig-Logsig Activation Function Combination

The MAE based on MSE for tansig-logsig recorded values close to zero within the first 90 VIUs as shown in Figure 4.40. This is an indication of good calibration. This was consistent with the MAE based on RMSE as in Figure 4.41. For Tansig-Logsig combination pair, the error in calibrating the user's parameters and their MAE is presented in Appendix H.

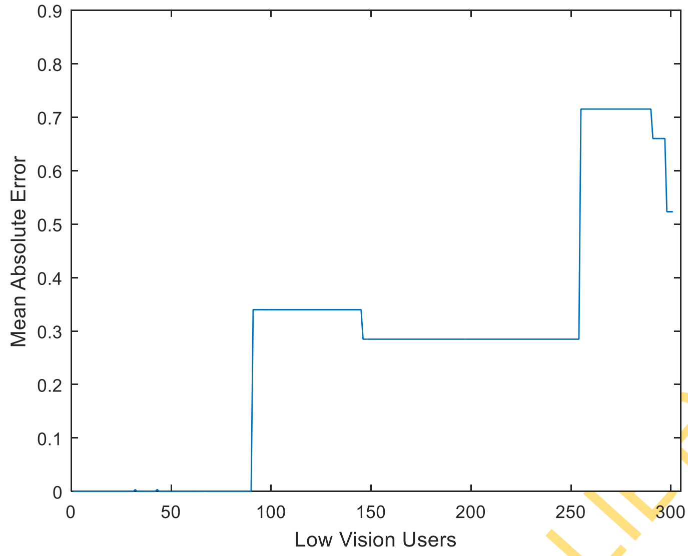

Figure 4.40. MAE for Tansig-Logsig Activation Function Combination based on MSE

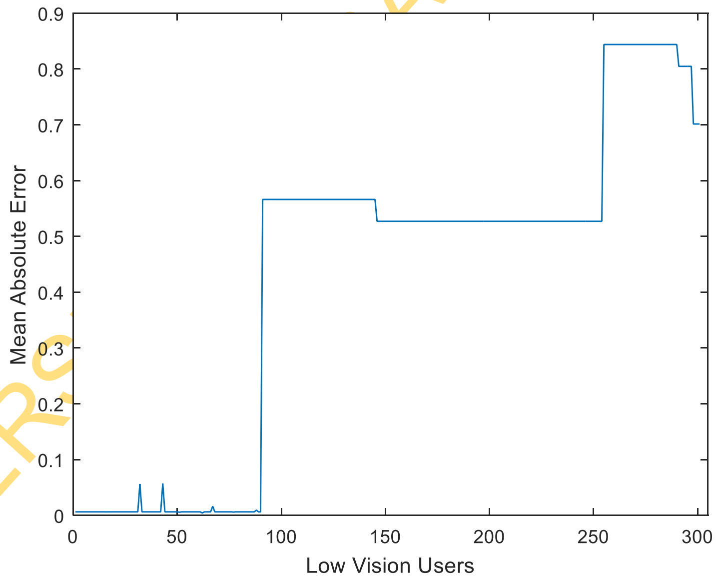

Figure 4.41. MAE for Tansig-Logsig Activation Function Combination based on RMSE

4.2.4.7. MAEs for Logsig-Purelin Activation Function Combination

The MAE based on MSE for logsig-purelin activation function combination recorded values below 0.3 for the first 250 VIUs with intermittent outliers as shown in Figure 4.42. Similarly, the MAE based on RMSE showed the same trends with slightly higher corresponding values as shown in Figure 4.43. The error for parametric calibration and MAE for Logsig-Purelin activation function combination is shown in Appendix I.

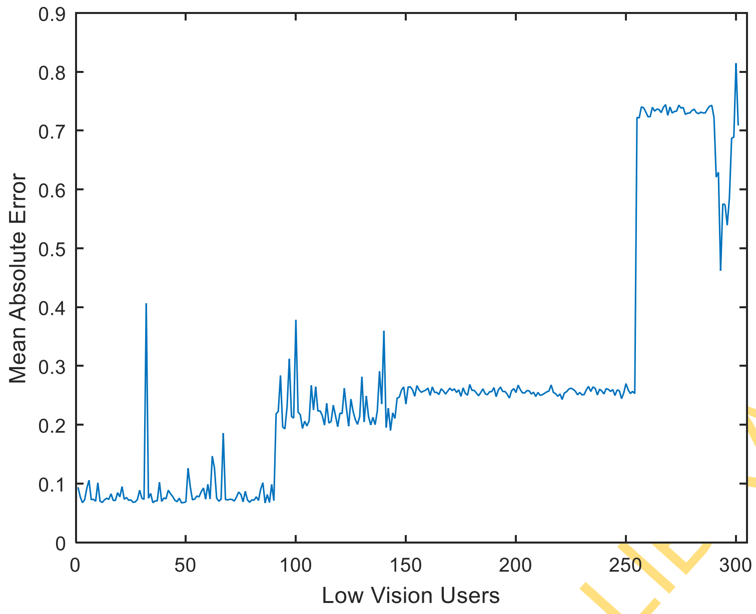

Figure 4.42. MAE for Logsig-Purelin Activation Function Combination based on MSE

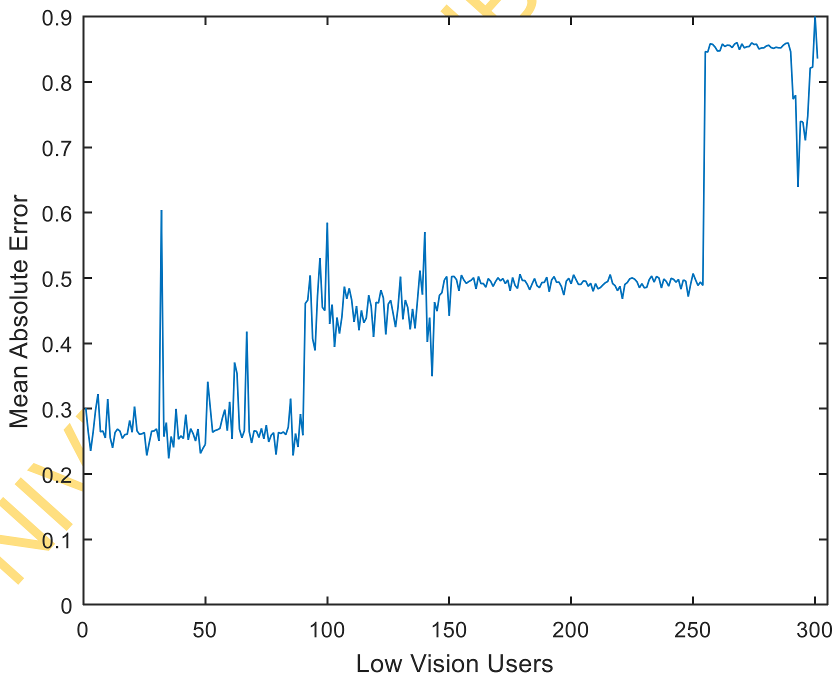

Figure 4.43. MAE for Logsig-Purelin Activation Function Combination based on RMSE

4.2.4.8. MAEs for Logsig-Tansig Activation Function Combination

The MAE based on MSE logsig-tansig activation function combination achieved least values within the first 90 LVUs with two pronounced outliers as in Figure 4.44. In Figure 4.45, the outliers were more extruded in the MAE based on RMSE. The parametric calibration error and MAE for Logsig-Tansig combination is in Appendix J.

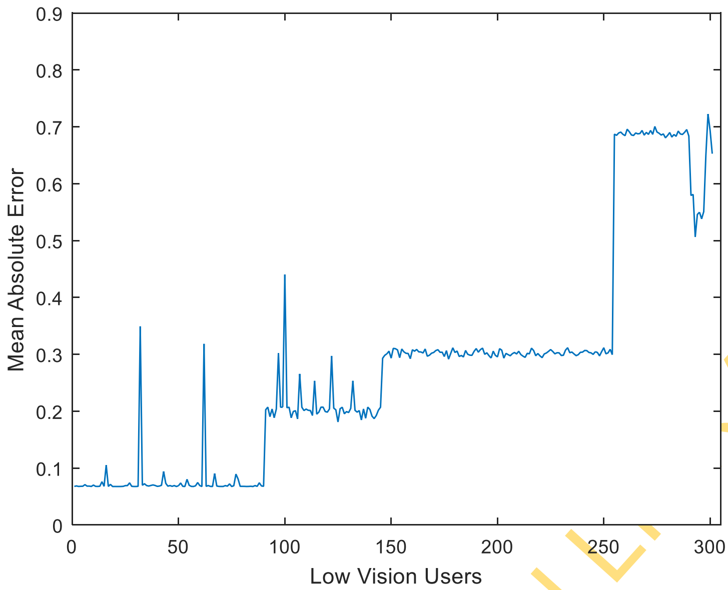

Figure 4.44. MAE for Logsig-Tansig Activation Function Combination based on MSE

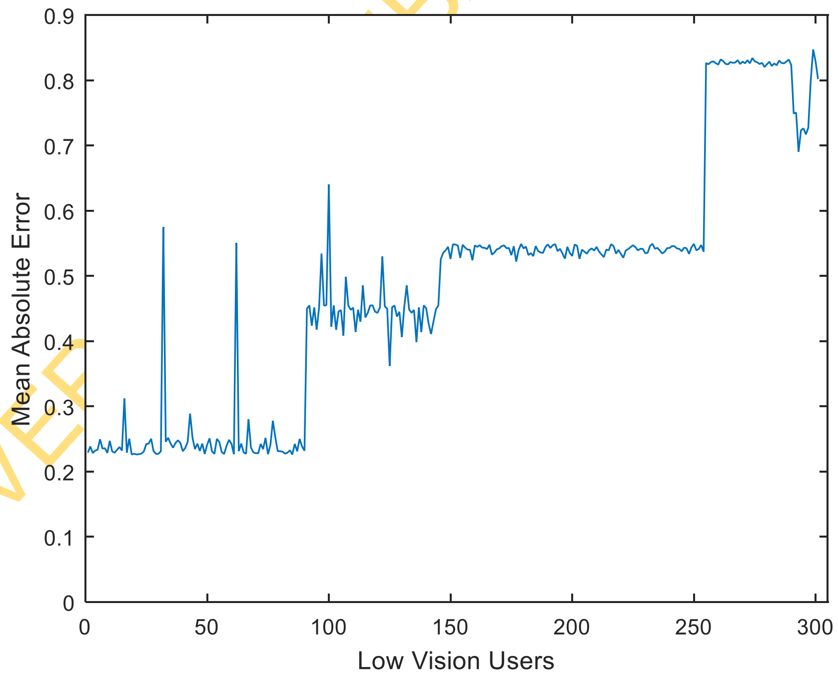

Figure 4.45. MAE for Logsig-Tansig Activation Function Combination based on RMSE

4.2.4.9. MAEs for Logsig-Logsig Activation Function Combination

The MAE based on MSE for logsig-logsig combination recorded two outliers as shown in Figure 4.46. Similar trend was achieved in the MAE based on RMSE as presented in Figure 4.47. Considering Logsig-Logsig activation function combination, the error in user's parameter calibration and associated MAE is shown in Appendix K.

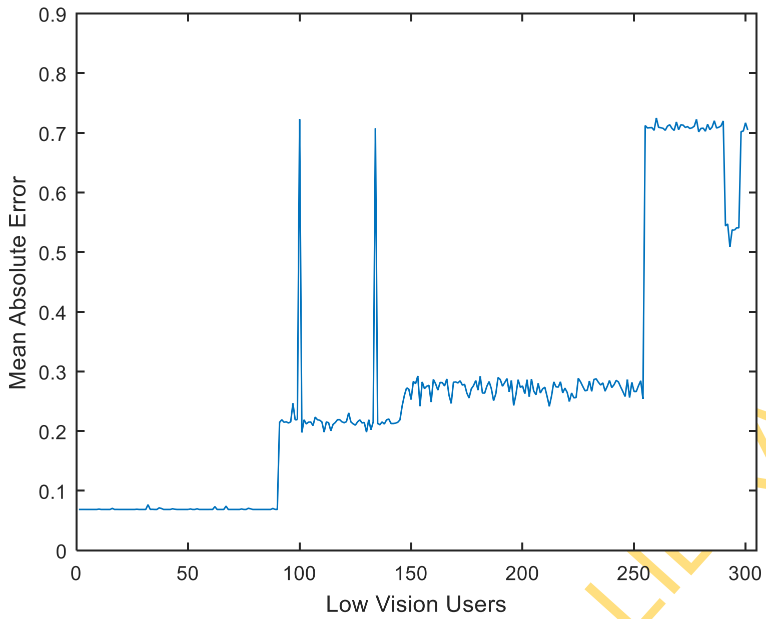

Figure 4.46. MAE for Logsig-Logsig Activation Function Combination based on MSE

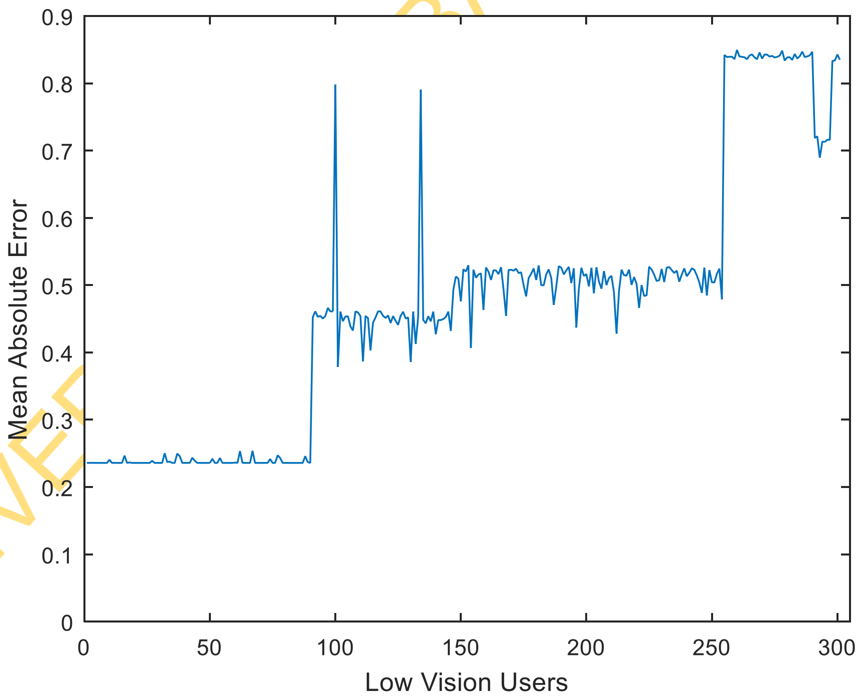

Figure 4.47. MAE for Logsig-Logsig Activation Function Combination based on RMSE

4.2.4.10.Comparative Analysis of the MAEs

In Figure 4.48, all the possible combinations of the activation functions were computed. The tansig-purelin pair attained the best calibration. The other activation functions followed similar calibration patterns with slight deviation from 90^{th} VIU to 145^{th} VIU.

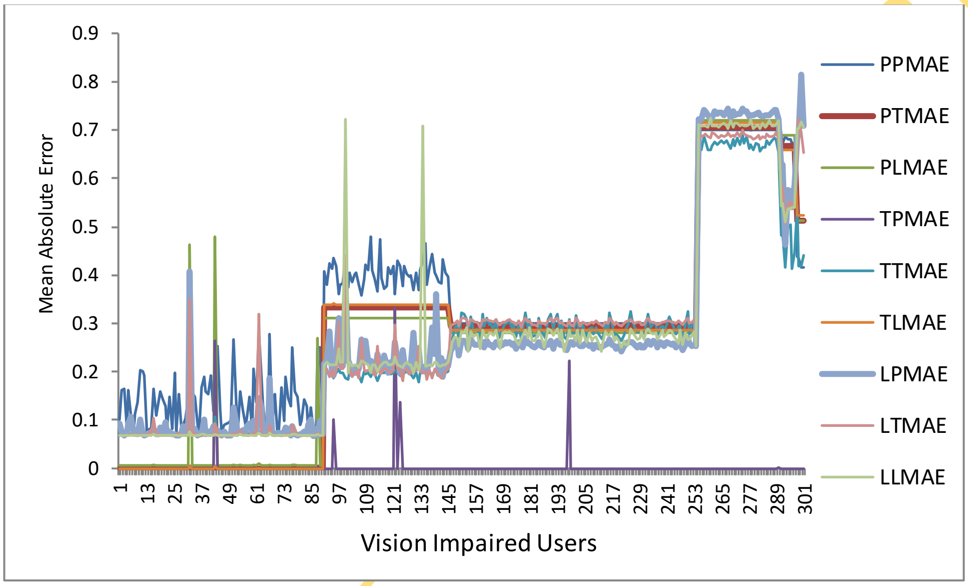

Figure 4.48. Comparative Analysis of the MAEs based on MSE

The performance evaluation of the activation function pairs and the Dynamic Thresholding Algorithm (DTA) is presented in Table 4.6. The metrics used in evaluating the performance are accuracy, correct rate, error rate, last correct rate, last error rate, inconclusive rate, classified rate, sensitivity, specificity, false positive rate and false negative rate. The performance evaluation report clearly indicates that all the VIUs were classified. There is no unclassified user in all. With reference to all the performance metrics, tansig-purelin (TP) activation function combination achieved the best values. The accuracy, sensitivity and specificity of TP pair are 99.6678%, 99.79% and 100%. With these values, the false positive rate of 0% and false negative rate of 0.21% were attained.

Table 4.6. Performance Evaluation of Activation Function Combinations and DTA

Activation Function Pair	Accuracy (%)	Correct Rate (%)	Error Rate (%)	Last Correct Rate (%)	Last Error Rate (%)	Inconclusive Rate (%)	Classified Rate (%)	Sensitivity (%)	Specificity (%)	False Positive Rate (%)	False Negative Rate (%)
PP	66.113	79.18	20.82	79.18	20.82	0	100	71.78	87.65	12.35	28.22
PT	66.113	79.51	20.49	79.51	20.49	0	100	71.37	88.84	11.16	28.63
PL	65.4485	79.29	20.71	79.29	20.71	0	100	70.95	88.84	11.16	29.05
TP	99.6	99.89	0.11	99.89	0.11	0	100	99.79	99.52	0.48	0.21
TT	75.0831	86.16	13.84	86.16	13.84	0	100	89.63	82.19	17.81	10.37
TL	66.113	79.51	20.49	79.51	20.49	0	100	71.37	88.84	11.16	28.63
LP	79.7342	84.05	15.95	84.05	15.95	0	100	80.29	88.36	11.64	19.71
LT	82.0598	84.83	15.17	84.83	15.17	0	100	82.16	87.89	12.11	17.84
LL	81.3953	84.05	15.95	84.05	15.95	0	100	82.57	85.75	14.25	17.43

4.3. Comparative Analysis of the Model

Besides the manual calibration of low vision aids, the existing assistive devices are statically configured that always needs manual reconfigurations for searching for the best calibrations to correct a particular vision defects. JAWS and ZoomText assistive devices are manually reconfigurable audio and visual assistive technologies respectively. Assistive technology with static configuration model arbitrarily has sensitivity and specificity values to be 0% or extremely low. However, an intelligent based adaptive reconfigurable assistive technology model was developed in this research work. The model is able to adaptively configure the calibration parameters to suit vision impairment requirements of a specific user. Sequel to the development of the model, ANN-based optimized mathematical model was developed. The model predicted sensitivity value of 99.79% and specificity value of 99.52% with dynamic thresholding model attaining accuracy of 99.6% at threshold value of 0.5.

CHAPTER FIVE

SUMMARY AND CONCLUSIONS

5.1. Summary

The challenge of existing web-based or e-learning technologies has been technical exclusion of visual impaired users (VIUs) due to platforms or architecture that does not suit specific and dynamic requirements of VIUs. This has led to frequent manual adjustment of e-learning platforms to the suitability of VIUs. The problem of arriving at the correct or medically suitable calibration for specific needs of VIUs arises at this point. Wrong calibrations have worsened the vision of many VIUs. Lack of adaptive and intelligent-based platforms is inhibiting users' accessibility and usability. In order to mitigate this challenge, an intelligent-based adaptive framework to access multimedia resources was developed. The specific requirements of each low acuity user were used as the basis of adaptive calibration parameters settings to develop the intelligent based dynamic vision calibrator.

The parameters that largely determine the effectiveness of vision in e-learning platforms are visual acuity, print size and reading rate. They are the input variables to the calibrator. The parameters upon which the adaptive calibrator is developed are connection weights (input and layer weights), summing function, activation function and error computation. The values of connection weights are randomly varied from 0 to 1 for optimal calibration. An adder module was used as the summing function. Nine pairs of activation functions were used in hidden and output layers. The three types of transfer functions that form these 9 pairs are tansig, purelin and logsig activation functions. The error computation was done based on two dimensions: Mean Squared Error (MSE) and Root Mean Squared Error (RMSE). Mean Absolute Error (MAE) was computed for all the 9 activation function pairs based on MSE and RMSE. In order to search for best calibration parameters, dynamic thresholding algorithm was developed. The threshold value with global maximum accuracy that gives global minimum deviation over repeated computation was used for best calibration performance. With this best threshold value, a three-bit based mathematical model was developed with independent variables as visual acuity, print size and reading rate of the VIU.

The developed calibrator was trained, validated, tested and evaluated using WHO visual impairment dataset grouping with level of vision from no visual impairment to complete blindness. The visual acuities of VIUs were included in the WHO dataset groupings with associated recommended assistive technologies. The dataset groupings were preprocessed into 3-bit representation for optimized calibration and modeling. The result of tansig-purelin activation function pair gives the best performance with the least MSE of 0.0037494, overall regression of 0.99647. The best calibration pair was derived through the developed calibration model. The threshold value of 0.5 gives the global maximum accuracy of 99.6% with consistent global minimum deviation of 0.156492159 on training dataset while it gives 97.5083% and 1.590411762 respectively on testing dataset. Further evaluation of the dynamic thresholding algorithm with MAE based on MSE and RMSE shows that tansig-purelin activation function combination pair has the best performance with least MSE, RMSE and MAE. Even though five outliers were recorded they are within acceptable values of less than 0.4 MAE. Based on eleven performance evaluation metrics, tansig-purelin activation function consistently achieved best performance. The accuracy, sensitivity and specificity of tansig-purelin combination are 99.6678%, 99.79% and 100%.

5.2. Conclusion

The intelligent-based calibrator for LVUs of e-learning platforms has dealt with the existing limitation of static or inadjustable calibration. With input variables of visual acuity, print size and reading rate, an adaptive calibrator was developed that dynamically re-calibrates the e-learning platform model for optimised access to resources. Among several other parametric settings, tansig-purelin activation function achieved best performance. The calibrator’s training, validation, testing and evaluation using WHO visual impairment dataset gives validity to the developed model.

5.3. Recommendations

This research work has been able to develop a dynamic calibrator of visual acuity. The deployment and integration of this algorithm into web-based technologies is recommended. For effective performance of the calibrator, continuous user calibration is also recommended from time to time. The future direction of this research with respect to application area is consideration device luminance for the development of assistive calibrator. Also, unsupervised artificial neural learning approach is another area of further research for enhancing the performance of adaptive calibrator in e-learning environment.

5.4. Contribution to Knowledge

The research established a three-bit encoding optimized dynamic thresholding model that can adaptively calibrate and classify various degree of visual impairment excluding total blindness users' access to electronic resources in e-learning environment.

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APPENDICES

Appendix A: MATLab codes for ANN-based model on testing dataset

```
clear all; clc; close all;

% Data feeding-in and saving section...
MyData=xlsread('TestingDataset302.xlsx');

% Input and Target Features extraction section...
InputData=MyData(:,1:3);
TargetData=MyData(:,4:end);

% Data transpose section in preparation for feeding into ANN
InputDataTranspose=InputData';
TargetDataTranspose=TargetData';

% ANN codes section...
net = newff(InputDataTranspose,TargetDataTranspose,10);
net = train(net,InputDataTranspose,TargetDataTranspose);
Output=net(InputDataTranspose);
Error=Output-TargetDataTranspose;
perf=perform(net,Output,TargetDataTranspose);

% Simulation with training data section...
SimResult=sim(net,InputDataTranspose);

% Thresholded Simulation with training data section...
ThreshSimResult=SimResult>0.5;

% Accuracy computation for Thresholded Simulation with training
% data section...

% Data source and sample result...
```

```
TargetData=TargetDataTranspose';
ThreshSimResult=ThreshSimResult';

[Accuracy]= AccuracyCompute(TargetData, ThreshSimResult)

% Computation of absolute difference between
% Grand truth and Result: element by element
% for n=1:1:400
%     for k=1:1:3
%     ksum(n,1)=abs(TargetData(n,k)-ThreshSimResult(n,k));
%     end
%
%
% end
%
% % Recalling the stored computed absolute difference
% for j=1:1:400
%     ksum(j,1)=ksum(j,1);
%
% end
%
% % Displaying the absolute difference matrix
% % between GrandTruth and Results
% % 0's are the ones that are the same
% % 1's are the ones that are different
% ksum(j,1)=ksum(j,1);
%
% % Computing the sum of the matrix
% TotalSum=sum(ksum)
%
% % Computing the accuracy of the analysis...
% TrainingDataAccuracy = (n-TotalSum)/n * 100
%
% % Simulation with testing data section...
```

```
%     % Uploading of TestData
%        MyTestData=xlsread('TESTING4DATAEXCEL.xlsx');
%
%        % Input and Target Features extraction section...
%        TestInputData=MyTestData(:,1:4);
%        TestTargetData=MyTestData(:,5:end);
%
%        % Data transpose section in preparation for feeding into ANN
%        TestInputDataTranspose=TestInputData';
%        TestTargetDataTranspose=TestTargetData';
%
%
%        % Simulation with training data section...
%        TestSimResult=sim(net,TestInputDataTranspose);
%
%
%        % Thresholded Simulation with testing data section...
%        ThreshTestSimResult=TestSimResult>0.5;
%
%
%
%        % Accuracy computation for Thresholded Simulation with testing
%        % data section...
%        % Data source and sample result...
%        ThreshTestSimResult=ThreshTestSimResult';
%
% % Computation of absolute difference between
% % Grand truth and Result: element by element
% for n=1:1:200
%     for k=1:1:3
%     ksum(n,1)=abs(TestTargetData(n,k)-ThreshTestSimResult(n,k));
%     end
%
%
```

```
% end
%
% % Recalling the stored computed absolute difference
% for j=1:1:200
%     ksum(j,1)=ksum(j,1);
%
% end
%
% % Displaying the absolute difference matrix
% % between GrandTruth and Results
% % 0's are the ones that are the same
% % 1's are the ones that are different
% ksum(j,1)=ksum(j,1);
%
% % Computing the sum of the matrix
% TotalSum=sum(ksum)
%
% % Computing the accuracy of the analysis...
% TestDataAccuracy = (n-TotalSum)/n * 100
```

Appendix B: Error computation and adjustment during model training

Visual Acuity (Va) Error	Print Size (Ps) Error	Reading Rate (Rr) Error
0.04141728	-0.147523089	0.139968937
0.06074536	-0.106422295	0.122465527
0.14902609	0.081305017	0.042518944
0.0100121	-0.214305619	0.168409312
0.02578212	-0.180770972	0.154128063
-0.0371312	-0.314554979	0.211102054
0.12601213	0.032366263	0.06336027
0.11035097	-0.000936907	0.077542941
0.04210619	-0.146058139	0.139345065
-0.0233898	-0.285334116	0.198657897
-0.0572931	-0.357428939	0.229360594
-0.0215796	-0.281484874	0.197018637
0.1358635	0.053315	0.054438926
0.07603374	-0.073911848	0.10862045
0.09684765	-0.029651469	0.089771482
-0.041462	-0.323764321	0.215023995
0.06105344	-0.105767179	0.122186536
0.07696079	-0.071940497	0.107780919
0.13931123	0.060646536	0.051316678
0.05922152	-0.109662717	0.123845511
0.13760732	0.057023212	0.052859727
0.10335237	-0.015819294	0.083880836
0.01781054	-0.197722382	0.161347083
-0.0618725	-0.367166886	0.233507649
0.0668192	-0.093506405	0.116965095
-0.0853516	-0.417094751	0.254770204
0.12232865	0.024533414	0.066696011
-0.0221561	-0.282710587	0.197540627
0.04729126	-0.135032199	0.134649498
-0.080449	-0.406669475	0.250330439

-0.0278804	-0.2948833	0.202724565
-0.0150577	-0.267616134	0.19111242
-0.0308488	-0.301195463	0.205412697
0.08861773	-0.047152241	0.097224457
0.00078381	-0.233929397	0.176766401
0.03750796	-0.155836199	0.143509204
-0.0691646	-0.382673448	0.240111359
0.06957389	-0.087648592	0.114470455
0.08816878	-0.048106925	0.097631024
0.13766829	0.057152857	0.052804516
0.13307052	0.04737578	0.056968235
0.15596332	0.096056894	0.036236629
0.00680983	-0.221115182	0.171309269
0.07401545	-0.078203704	0.110448203
-0.0292909	-0.297882782	0.204001941
-0.0330729	-0.305925069	0.207426873
-0.0310458	-0.301614402	0.205591109
-0.0784013	-0.402315003	0.248476019
0.04723711	-0.13514733	0.134698528
-0.0741543	-0.393283965	0.244630012
0.08090137	-0.063560931	0.104212351
0.13981993	0.061728286	0.050855998
0.03616547	-0.158690981	0.144724957
0.10435752	-0.013681862	0.082970577
-0.0536682	-0.349720493	0.226077833
-0.0041406	-0.244401025	0.181225906
-0.0322936	-0.304267802	0.2067211
0.08502374	-0.05479478	0.10047915
-0.0982362	-0.444493619	0.266438436
0.07720548	-0.07142017	0.10755933
0.12120583	0.022145753	0.067712833
-0.0792668	-0.404155423	0.249259791
0.11441273	0.007700347	0.073864633

0.01040795	-0.213463859	0.168050835
-0.0616091	-0.366606728	0.233269097
0.05210797	-0.124789557	0.13028751
-0.0049339	-0.246088021	0.18194434
0.14743539	0.077922414	0.043959478
-0.0259663	-0.290813016	0.200991172
-0.0189818	-0.275960689	0.194666078
-0.0378906	-0.316169914	0.211789799
0.10662013	-0.00887046	0.080921568
-0.0259013	-0.290674741	0.200932285
0.01013991	-0.214033841	0.168293571
0.15139886	0.086350661	0.040370178
0.09771086	-0.027815855	0.088989757
-0.0764987	-0.398269142	0.246753027
0.00231916	-0.23066451	0.175375998
0.15481691	0.093619083	0.037274808
-0.0466924	-0.334886696	0.219760631
-0.0013539	-0.238475272	0.178702333
-0.0317722	-0.303159182	0.206248978
0.05914201	-0.109831785	0.123917511
0.04753233	-0.134519566	0.134431185
0.09427004	-0.035132704	0.092105751
-0.0006347	-0.236945847	0.178051003
0.12502021	0.030256951	0.064258553
0.04679401	-0.136089587	0.135099803
0.06244589	-0.102806146	0.120925534
-0.0356074	-0.311314537	0.209722062
0.11828522	0.015935121	0.070357726
-0.0716943	-0.388052806	0.242402242
0.06558974	-0.096120822	0.118078485
0.12037522	0.020379474	0.06846503
-0.0662676	-0.376512886	0.237487788
-0.001541	-0.238873011	0.178871716

-0.0193643	-0.276774032	0.195012452
-0.0478246	-0.337294375	0.220785978
-0.011923	-0.260950114	0.188273592
0.09959236	-0.023814897	0.087285887
0.1275437	0.035623119	0.061973288
-0.0710808	-0.38674808	0.241846604
0.13691745	0.055556213	0.053484471
0.05614963	-0.116195032	0.126627398
-0.0408236	-0.322406795	0.214445871
-0.0745369	-0.394097456	0.24497645
0.00215879	-0.231005536	0.17552123
-0.0197774	-0.277652496	0.19538656
-0.0780482	-0.40156426	0.248156304
-0.0270032	-0.293018047	0.201930218
-0.0429068	-0.326836575	0.216332362
0.09371341	-0.036316367	0.092609832
0.04877462	-0.13187786	0.133306174
-0.0124808	-0.262136449	0.188778811
0.01852047	-0.196212725	0.160704172
0.13050077	0.04191127	0.059295381
0.02610941	-0.180075003	0.153831674
0.1280694	0.036741011	0.061497216
0.01112024	-0.211949187	0.167405789
0.15422118	0.092352257	0.037814306
0.13652738	0.05472673	0.053837719
0.06479953	-0.09780119	0.118794096
-0.0280223	-0.295184989	0.202853044
0.06666432	-0.093835743	0.117105349
0.1025053	-0.017620576	0.08464794
0.0155144	-0.20260509	0.16342646
-0.0016343	-0.239071405	0.178956205
-0.0628619	-0.369270744	0.23440361
0.01170103	-0.210714144	0.166879826

-0.0836167	-0.413405541	0.253199097
0.04686438	-0.135939946	0.135036076
0.09117587	-0.041712404	0.094907818
0.16062147	0.105962369	0.032018229
0.10857831	-0.004706435	0.079148253
-0.0838427	-0.413886181	0.253403785
-0.0527702	-0.347811032	0.225264659
0.1363853	0.054424612	0.053966381
0.09065461	-0.042820855	0.095379869
-0.0145924	-0.266626645	0.190691031
0.06505158	-0.097265209	0.11856584
0.0369105	-0.157106678	0.144050256
-0.0435734	-0.328254261	0.216936105
-0.0214623	-0.281235382	0.196912388
-0.0007744	-0.237242927	0.178177519
-0.0277935	-0.294698519	0.202645873
0.08884516	-0.046668614	0.097018497
0.01627623	-0.200985065	0.162736547
0.14532646	0.073437823	0.04586931
-0.015908	-0.269424158	0.191882395
0.11729679	0.013833255	0.071252839
0.0137345	-0.206390003	0.165038324
0.12524155	0.030727635	0.064058105
0.08950932	-0.045256282	0.096417033
0.00558839	-0.223712559	0.172415403
0.11017187	-0.001317764	0.077705135
0.09028219	-0.043612785	0.095717125
-0.0724125	-0.389579931	0.243052592
0.10510672	-0.012088709	0.082292109
0.01156434	-0.211004823	0.167003617
0.14672127	0.076403848	0.044606183
0.08663195	-0.051374958	0.099022766
-0.0974981	-0.442923961	0.265769973

0.10284365	-0.016901083	0.084341532
-0.0919908	-0.431212789	0.260782589
0.07983246	-0.065833941	0.105180348
0.01941166	-0.194317645	0.159897123
-0.0709994	-0.386575083	0.241772931
-0.0596528	-0.362446791	0.231497524
0.00802845	-0.218523808	0.170205693
0.03922089	-0.152193678	0.141957979
-0.0197834	-0.277665106	0.19539193
0.11085597	0.00013696	0.077085618
0.09593154	-0.031599549	0.090601102
0.02197876	-0.188858737	0.157572363
-0.0278265	-0.294768757	0.202675785
0.1085661	-0.004732395	0.079159309
0.06935041	-0.088123834	0.114672844
-0.0171448	-0.272054164	0.193002424
-0.0340889	-0.308085501	0.208346927
0.03242055	-0.166654466	0.14811633
0.03844923	-0.153834603	0.142656793
0.07864542	-0.068358154	0.106255323
-0.015588	-0.268743817	0.191592661
-0.008059	-0.252733539	0.184774436
-0.0026321	-0.241193371	0.179859877
0.13065619	0.042241767	0.059154634
0.03126322	-0.169115521	0.149164409
0.13484162	0.051141995	0.055364334
0.13668694	0.055066027	0.053693224
0.06755535	-0.091940984	0.116298437
0.1246693	0.02951075	0.064576335
0.0511696	-0.126784982	0.131137293
0.07696881	-0.07192344	0.107773655
0.03474344	-0.161714888	0.146012734
0.13610647	0.053831682	0.054218889

-0.0651454	-0.374126647	0.236471571
0.10476626	-0.012812679	0.082600422
0.10568699	-0.010854762	0.081766613
-0.0681429	-0.380500778	0.239186094
0.00405268	-0.226978207	0.173806129
0.13546069	0.05245843	0.05480371
0.01254981	-0.208909239	0.16611118
0.1299408	0.040720499	0.05980249
0.00130309	-0.23282516	0.176296145
0.09185996	-0.040257697	0.094288308
0.13088566	0.042729725	0.058946829
-0.0248057	-0.288344952	0.199940108
0.05861288	-0.110956982	0.124396694
0.10163878	-0.019463213	0.085432655
-0.1703022	0.402259506	-0.668299009
-0.1082796	0.534149311	-0.724466325
-0.1704749	0.401892226	-0.668142597
-0.1885106	0.363539578	-0.651809528
-0.1690747	0.404869729	-0.669410613
-0.122948	0.502957217	-0.711182688
-0.0983051	0.555359893	-0.73349918
-0.1582061	0.427981617	-0.679253168
-0.0990647	0.553744673	-0.732811313
-0.1342792	0.478861611	-0.700921201
-0.1007509	0.550158932	-0.73128427
-0.0908826	0.571143606	-0.740220918
-0.105319	0.540444896	-0.727147397
-0.1245527	0.499544803	-0.709729459
-0.1925659	0.35491607	-0.648137073
-0.1294167	0.489201605	-0.705324648
-0.0771973	0.600245266	-0.752614311
-0.1914397	0.357310823	-0.649156916
-0.1842712	0.372554623	-0.655648724

-0.2178229	0.301207635	-0.625264504
-0.1490722	0.447404643	-0.687524764
-0.1779494	0.385997853	-0.661373732
-0.153959	0.43701283	-0.68309925
-0.2099149	0.318023692	-0.632425883
-0.1008489	0.549950464	-0.73119549
-0.2475458	0.238002465	-0.598347604
-0.1197425	0.509773591	-0.714085547
-0.1118604	0.526534869	-0.721223597
-0.1168993	0.515819577	-0.716660323
-0.2054958	0.327420885	-0.636427823
-0.1517322	0.441748125	-0.685115848
-0.1556232	0.433473945	-0.681592161
-0.1418212	0.462823762	-0.694091235
-0.1794798	0.382743477	-0.659987805
-0.0967662	0.558632352	-0.734892807
-0.1710641	0.400639353	-0.667609041
-0.0941384	0.564220358	-0.737272546
-0.2089405	0.32009582	-0.63330833
-0.234622	0.265484515	-0.610051261
-0.1436784	0.458874497	-0.69240938
-0.1032331	0.544880525	-0.729036378
-0.1795628	0.382566971	-0.659912637
-0.1309882	0.485859998	-0.703901573
-0.2347715	0.265166744	-0.609915933
-0.1565145	0.431578652	-0.680785021
-0.1355533	0.476152403	-0.699767443
-0.1646795	0.414215982	-0.673390859
-0.1852362	0.370502611	-0.654774843
-0.1229241	0.503008105	-0.71120436
-0.1273125	0.493676142	-0.707230199
-0.2086614	0.320689358	-0.633561098
-0.1225353	0.503834761	-0.711556404

-0.1498231	0.445807832	-0.686844738
-0.1897886	0.360821946	-0.650652182
-0.1015185	0.548526702	-0.73058916
-0.233335	0.268221411	-0.61121681
-0.1899771	0.360421113	-0.650481481
-0.155795	0.433108621	-0.681436582
-0.2360585	0.262429865	-0.608750391
-0.1331662	0.481228414	-0.701929141
-0.1340112	0.479431562	-0.701163924
-0.1970694	0.345339401	-0.644058701
-0.2457428	0.241836398	-0.599980344
-0.0912105	0.570446533	-0.739924059
-0.1397271	0.467276801	-0.695987631
-0.1258313	0.496825969	-0.708571602
-0.2055311	0.327345735	-0.636395819
-0.198297	0.342728916	-0.642946985
-0.1771962	0.387599546	-0.662055838
-0.1341459	0.479145062	-0.701041914
-0.1782782	0.385298523	-0.661075912
-0.1874408	0.36581445	-0.652778317
-0.237719	0.258898945	-0.607246694
-0.0833202	0.587225024	-0.747069439
-0.1021628	0.547156658	-0.730005705
-0.1551523	0.434475498	-0.682018688
-0.1311496	0.485516605	-0.703755334
-0.1374436	0.472132628	-0.69805556
-0.1938693	0.352144396	-0.646956713
-0.1384345	0.470025512	-0.697158212
-0.1756636	0.390858487	-0.663443708
-0.1559861	0.432702362	-0.68126357
-0.1684946	0.406103268	-0.669935934
-0.1964671	0.346620231	-0.644604162
-0.135548	0.476163551	-0.699772191

-0.1152556	0.519314915	-0.718148867
-0.1457117	0.454550654	-0.690568004
-0.2218066	0.292736375	-0.621656887
-0.1073058	0.536220085	-0.725348196
-0.1964504	0.346655758	-0.644619292
-0.2006054	0.337820226	-0.640856543
-0.1238496	0.501040048	-0.710366233
-0.1958592	0.347912862	-0.645154649
-0.2002993	0.338471063	-0.641133713
-0.211644	0.314346956	-0.630860088
-0.1479923	0.449701087	-0.688502741
-0.2044631	0.329617	-0.637363072
-0.1548175	0.43518735	-0.682321841
-0.1495299	0.446431394	-0.687110291
-0.0998398	0.552096369	-0.732109357
-0.0988541	0.554192439	-0.733002001
-0.1621331	0.419630904	-0.675696888
-0.1681732	0.406786732	-0.670226998
-0.1137185	0.522583549	-0.719540866
-0.2098647	0.318130421	-0.632471335
-0.1516577	0.441906541	-0.685183313
-0.2096212	0.31864825	-0.63269186
-0.1507894	0.443753125	-0.685969709
-0.2058088	0.326755348	-0.636144394
-0.2074953	0.32316898	-0.634617083
-0.1415285	0.463446204	-0.694356312
-0.1244007	0.499868104	-0.709867142
-0.1793475	0.383024797	-0.66010761
-0.2230193	0.290157502	-0.620558634
-0.2075392	0.323075699	-0.634577358
-0.183648	0.373879927	-0.656213126
-0.2297062	0.275937993	-0.614503036
-0.1144023	0.521129417	-0.718921601

-0.1619846	0.419946677	-0.675831364
-0.1290937	0.489888476	-0.705617163
-0.1151191	0.51960516	-0.718272473
-0.1633267	0.417092711	-0.674615959
-0.1240922	0.500524044	-0.710146484
-0.1881426	0.364322176	-0.652142809
-0.0772725	0.600085375	-0.752546219
-0.1649765	0.413584467	-0.673121919
-0.1747299	0.392844068	-0.664289299
-0.2266406	0.28245679	0.382720833
-0.2277902	0.280012192	0.383761903
-0.2769716	0.175429021	0.428300266
-0.2330554	0.268815941	0.38853
-0.2513245	0.229967027	0.405074412
-0.2447192	0.244013097	0.399092676
-0.2356446	0.263309975	0.390874801
-0.2344311	0.265890533	0.38977583
-0.2701816	0.189867826	0.422151278
-0.2716133	0.186823276	0.423447846
-0.225433	0.285024907	0.381627161
-0.2540838	0.224099488	0.407573194
-0.2379966	0.258308627	0.393004703
-0.2688365	0.192727992	0.420933232
-0.2615464	0.208230301	0.414331333
-0.2690966	0.192175011	0.421168727
-0.2439321	0.245686906	0.398379858
-0.2591537	0.213318289	0.412164535
-0.26251	0.206181347	0.415203912
-0.2429658	0.247741619	0.397504826
-0.2454413	0.242477568	0.399746604
-0.2604697	0.210520007	0.413356227
-0.2651958	0.20046999	0.417636182
-0.2547624	0.222656311	0.408187794

-0.2571729	0.217530465	0.410370715
-0.238063	0.258167412	0.393064841
-0.2438514	0.245858526	0.398306771
-0.2574971	0.216841109	0.410664287
-0.240057	0.253927253	0.394870578
-0.244182	0.245155435	0.398606193
-0.2650887	0.200697803	0.417539164
-0.2365609	0.261361604	0.391704545
-0.2718474	0.186325535	0.423659817
-0.2568089	0.218304592	0.41004104
-0.2471264	0.238894295	0.401272596
-0.2342024	0.266376839	0.389568729
-0.270285	0.189647815	0.422244973
-0.253	0.226404175	0.406591708
-0.2703433	0.189523846	0.422297767
-0.2503044	0.232136178	0.404150645
-0.2383986	0.257453648	0.393368809
-0.2622392	0.20675712	0.41495871
-0.2510756	0.230496302	0.404849012
-0.2696464	0.191005763	0.42166667
-0.251048	0.230555004	0.404824013
-0.2735339	0.182739244	0.425187095
-0.2489192	0.235081847	0.402896187
-0.2356063	0.263391554	0.39084006
-0.2355157	0.263584234	0.390758004
-0.2438751	0.245808049	0.398328267
-0.2408566	0.252226772	0.395594754
-0.2550499	0.222045016	0.408448123
-0.2298149	0.275706869	0.385595392
-0.2691848	0.191987443	0.421248606
-0.2567056	0.218524248	0.409947496
-0.2560935	0.219825733	0.409393239
-0.2583575	0.215011419	0.411443489

-0.2653153	0.200215774	0.417744443
-0.2657895	0.199207433	0.418173861
-0.27756	0.174177736	0.428833145
-0.2490425	0.234819759	0.403007801
-0.2691974	0.191960546	0.421260061
-0.2629966	0.205146613	0.41564457
-0.2510864	0.230473382	0.404858773
-0.2546529	0.222889152	0.408088634
-0.2494527	0.233947399	0.403379309
-0.2383469	0.257563752	0.393321919
-0.2621082	0.207035786	0.414840036
-0.25777	0.216260818	0.410911413
-0.2720697	0.185852766	0.423861153
-0.249175	0.234537884	0.403127842
-0.2436676	0.24624923	0.398140384
-0.2409488	0.252030708	0.395678252
-0.2554665	0.221159037	0.408825431
-0.2798826	0.16923877	0.430936481
-0.2357614	0.263061612	0.39098057
-0.2618531	0.207578261	0.414609014
-0.262541	0.206115329	0.415232027
-0.2448387	0.24375897	0.399200899
-0.2296933	0.275965313	0.385485329
-0.2651171	0.200637416	0.417564881
-0.2812323	0.166368582	0.432158795
-0.2591275	0.213374165	0.412140739
-0.2515149	0.229562153	0.405246834
-0.2475515	0.237990296	0.401657578
-0.2581951	0.215356913	0.411296355
-0.2639425	0.20313511	0.416501199
-0.2623542	0.206512663	0.415062816
-0.2510015	0.230653786	0.404781945
-0.2664785	0.197742366	0.418797783

-0.2549958	0.222159992	0.408399158
-0.263066	0.204998887	0.415707481
-0.2465026	0.240220602	0.400707768
-0.2517822	0.228993663	0.405488934
-0.2669012	0.196843423	0.419180612
-0.2511358	0.230368248	0.404903546
-0.2541973	0.223858175	0.407675961
-0.2540215	0.224231808	0.407516844
-0.2505962	0.231515752	0.404414863
-0.2701279	0.189981889	0.422102702
-0.2565197	0.218919583	0.409779137
-0.2390087	0.256156428	0.39392125
-0.2481363	0.236746667	0.402187197
-0.2640236	0.202962526	0.416574697
-0.2458612	0.241584618	0.400126881
-0.2784963	0.172186794	0.429681019
-0.2402554	0.253505359	0.395050249
-0.2609177	0.209567248	0.413761974
-0.2571374	0.217606031	0.410338533
-0.2692701	0.191806071	0.421325846
-0.271818	0.186387896	0.423633259
-0.2557209	0.220618094	0.4090558
-0.2687785	0.192851483	0.420880641
-0.2764861	0.176461287	0.42786066
-0.2821434	0.164431209	0.432983855
-0.240217	0.253586863	0.395015539
-0.2369116	0.260615758	0.392022175
-0.2687172	0.19298168	0.420825195
-0.2513974	0.229811981	0.405140441
-0.23237	0.27027333	0.387909348
-0.269998	0.190258096	0.421985075
-0.2687329	0.192948301	0.42083941
-0.2617547	0.207787442	0.414519932

-0.2415372	0.250779449	0.39621112
-0.2306986	0.273827696	0.386395666
-0.2573107	0.217237423	0.410495511
-0.2756549	0.178228842	0.427107919
-0.2474323	0.238243766	0.401549634
-0.247555	0.237982732	0.4016608
-0.2763754	0.176696701	0.427760405
-0.2731583	0.183537775	0.424847028
-0.2505894	0.231530261	0.404408684
-0.2532513	0.225869707	0.406819319
-0.255868	0.220305389	0.40918897
-0.2699937	0.190267395	0.421981115
-0.2323379	0.270341636	0.387880259
-0.2515299	0.229530304	0.405260397
-0.2567555	0.21841805	0.409992722
-0.2458639	0.241578887	0.400129321
-0.2540298	0.224214267	0.407524314
-0.2295989	0.276166154	0.385399798
-0.2692913	0.191760983	0.421345048
-0.2341514	0.26648522	0.389522574
-0.2482765	0.236448584	0.40231414
-0.2725203	0.18489452	0.424269237
-0.2689772	0.192428915	0.421060598
-0.2456048	0.242129825	0.399894696
-0.268166	0.194153927	0.420325975
-0.2799804	0.169030749	0.431025069
-0.2446153	0.244234044	0.398998582
-0.2670125	0.196606876	0.419281349
-0.2312858	0.272578963	0.386927459
-0.2783581	0.17248053	0.429555927
-0.2425436	0.248639499	0.39712245
-0.2625291	0.206140751	0.4152212
-0.2503063	0.232132131	0.404152369

-0.2572953	0.217270178	0.410481561
-0.2714144	0.187246307	0.423267692
-0.2415745	0.250700197	0.39624487
-0.2454982	0.242356644	0.399798101
-0.2543832	0.223462784	0.407844345
-0.2523435	0.227800102	0.40599723
-0.2551177	0.221900759	0.408509557
-0.2606384	0.210161213	0.413509024
-0.2562229	0.219550672	0.409510378
-0.2413218	0.251237571	0.396016021
-0.2366566	0.261158107	0.391791207
-0.2577809	0.216237567	0.410921315
-0.2550073	0.222135565	0.408409561
-0.2421138	0.249553426	0.39673324
-0.2825065	0.163659181	0.433312635
-0.2511447	0.230349351	0.404911593
-0.252677	0.227090935	0.40629924
-0.2584953	0.214718426	0.411568265
-0.2421774	0.249418115	0.396790865
-0.2316217	0.271864604	0.38723168
-0.2433802	0.246860383	0.397880114
-0.2586903	0.214303728	0.41174487
-0.2608358	0.209741368	0.413687822
-0.2551657	0.221798835	0.408552963
-0.2607867	0.209845848	0.413643328
-0.2528536	0.226715345	0.406459191
-0.2331943	0.268520585	0.388655782
-0.2556762	0.220713152	0.409015318
-0.2742897	0.18113191	0.425871603
0.68351495	0.091404343	-0.535916523

Appendix C: Error computation for purelin – purelin activation parameters

Va Error	Ps Error	Rr Error	MAE
-0.20641	-0.08724	0.010202	0.101284975
-0.00503	0.296213	-0.18535	0.162198623
-0.00291	0.300254	-0.18741	0.163525106
-0.18582	-0.04804	-0.00979	0.08121874
-0.00388	0.298408	-0.18647	0.162919089
-0.21336	-0.10048	0.016952	0.110264776
-0.1458	0.028162	-0.04865	0.074205534
-0.08665	0.140791	-0.10609	0.111178328
-0.23356	-0.13894	0.036567	0.136356446
0.029959	0.362842	-0.21933	0.204043596
0.027279	0.357739	-0.21673	0.200581925
0.021571	0.34687	-0.21118	0.193208619
-0.14714	0.025606	-0.04735	0.073366495
-0.13394	0.05075	-0.06017	0.081620421
-0.17208	-0.02188	-0.02313	0.072363577
-3.52E-05	0.305728	-0.1902	0.165322135
-0.21231	-0.09848	0.015931	0.108906979
-0.03696	0.235425	-0.15435	0.142243712
-0.01113	0.284601	-0.17943	0.158386844
-0.03777	0.233881	-0.15356	0.141736732
-0.06038	0.190826	-0.13161	0.127603303
-0.18687	-0.05004	-0.00877	0.081894975
-0.02967	0.249296	-0.16142	0.146797207
-0.13275	0.053015	-0.06133	0.082364056
0.025712	0.354755	-0.21521	0.198557155
-0.17494	-0.02732	-0.02036	0.074206845
-0.01953	0.268601	-0.17127	0.153134268
-0.18135	-0.03952	-0.01414	0.078334057
-0.19479	-0.06512	-0.00108	0.086997402
-0.09895	0.117369	-0.09415	0.103489304
-0.02955	0.249519	-0.16154	0.146870434

0.083038	0.463914	-0.27087	0.272608246
-0.01578	0.275745	-0.17491	0.155479543
-0.02758	0.253275	-0.16345	0.148103496
-0.11708	0.082852	-0.07654	0.092158659
-0.15728	0.006311	-0.03751	0.067032429
0.002361	0.310292	-0.19253	0.168394511
0.018285	0.340613	-0.20799	0.188963861
-0.00852	0.289566	-0.18196	0.160016689
-0.01846	0.270652	-0.17232	0.153807814
0.020789	0.345381	-0.21043	0.192198654
-0.07824	0.156814	-0.11426	0.116437939
0.052994	0.406706	-0.2417	0.233799913
0.068668	0.436551	-0.25692	0.25404584
-0.07268	0.1674	-0.11966	0.119913113
-0.14279	0.033891	-0.05157	0.076086052
-0.19781	-0.07087	0.001849	0.090174591
-0.11601	0.084887	-0.07758	0.092826701
-0.11218	0.092188	-0.0813	0.095223265
-0.2054	-0.08532	0.009218	0.099976549
0.07795	0.454226	-0.26593	0.266036479
-0.0471	0.216114	-0.1445	0.135904591
-0.16722	-0.01263	-0.02785	0.069235014
-0.01035	0.286092	-0.18019	0.158876071
-0.07376	0.165339	-0.11861	0.119236446
-0.12195	0.073585	-0.07182	0.089116493
-0.10028	0.114851	-0.09286	0.102662962
-0.02546	0.257306	-0.16551	0.149426725
-0.13874	0.041608	-0.05551	0.078619233
0.031374	0.365537	-0.2207	0.205871956
-0.04653	0.217185	-0.14505	0.136256102
0.09066	0.478428	-0.27827	0.282454038
0.016085	0.336424	-0.20586	0.18612237
-0.05155	0.207628	-0.14018	0.133118944

-0.12974	0.058739	-0.06425	0.084243041
-0.09264	0.129389	-0.10028	0.107435223
0.08749	0.472392	-0.2752	0.27835992
-0.12813	0.061809	-0.06581	0.085250569
-0.01986	0.267973	-0.17095	0.152928342
-0.15278	0.014871	-0.04187	0.069842278
-0.18432	-0.04518	-0.01125	0.080247851
-0.25847	-0.18638	0.060758	0.16853586
-0.10875	0.098721	-0.08464	0.097367892
0.0177	0.3395	-0.20743	0.188208493
-0.0332	0.242577	-0.158	0.144591577
-0.22783	-0.12803	0.030999	0.12895006
0.066117	0.431694	-0.25444	0.250750784
-0.00928	0.288116	-0.18122	0.159540579
-0.02681	0.254747	-0.1642	0.148586553
-0.11975	0.077771	-0.07395	0.090490432
-0.20326	-0.08125	0.007145	0.097219037
-0.03528	0.238617	-0.15598	0.14329154
-0.05787	0.195596	-0.13404	0.129169036
-0.17668	-0.03063	-0.01867	0.075326009
-0.06102	0.189593	-0.13098	0.127198498
-0.18101	-0.03888	-0.01446	0.078116351
-0.19383	-0.06329	-0.00202	0.086376483
0.064994	0.429555	-0.25335	0.24930003
0.065655	0.430815	-0.25399	0.250154611
-0.14832	0.023369	-0.04621	0.072631863
0.149359	-0.4098	0.664724	0.407960398
0.195619	-0.32171	0.619801	0.379043664
0.123417	-0.4592	0.689915	0.424176155
0.142338	-0.42317	0.671541	0.412348718
0.104902	-0.49445	0.707894	0.435749389
0.131743	-0.44334	0.68183	0.418971487
0.226922	-0.2621	0.589404	0.359476832

0.193173	-0.32637	0.622177	0.380572733
0.189072	-0.33418	0.626159	0.383136073
0.096508	-0.51044	0.716046	0.440996768
0.203201	-0.30727	0.612438	0.374303997
0.154661	-0.3997	0.659575	0.404646125
0.183916	-0.344	0.631166	0.386359292
0.160201	-0.38915	0.654195	0.40118291
0.153718	-0.4015	0.66049	0.405235306
0.193177	-0.32636	0.622173	0.380569998
0.231015	-0.25431	0.585429	0.35691786
0.178499	-0.35431	0.636426	0.389745124
0.12988	-0.44689	0.683639	0.420136111
0.145347	-0.41744	0.668619	0.410467763
0.036327	-0.62503	0.774486	0.47861485
0.146313	-0.4156	0.667681	0.409864217
0.178376	-0.35454	0.636546	0.389821958
0.216746	-0.28148	0.599285	0.365837381
0.046008	-0.6066	0.765085	0.472563593
0.170219	-0.37008	0.644467	0.394920788
0.205646	-0.30262	0.610064	0.372775872
0.19944	-0.31443	0.61609	0.37665492
0.135166	-0.43682	0.678506	0.416831942
0.159101	-0.39125	0.655263	0.401870313
0.133129	-0.4407	0.680484	0.418105554
0.226289	-0.26331	0.590019	0.35987251
0.114461	-0.47625	0.698612	0.429774632
0.132108	-0.44265	0.681475	0.418743366
0.197787	-0.31758	0.617696	0.377688628
0.131025	-0.44471	0.682527	0.419420694
0.158384	-0.39261	0.65596	0.402319023
0.169371	-0.37169	0.64529	0.395450637
0.163364	-0.38313	0.651123	0.399205623
0.211442	-0.29158	0.604436	0.369152887

0.153443	-0.40202	0.660757	0.405407023
0.213623	-0.28743	0.602318	0.367789752
0.146754	-0.41476	0.667253	0.409588195
0.115634	-0.47402	0.697473	0.429041229
0.057677	-0.58438	0.753754	0.465269642
0.194581	-0.32369	0.620809	0.379692294
0.135351	-0.43647	0.678326	0.416716223
0.094199	-0.51483	0.718288	0.442439673
0.156379	-0.39643	0.657907	0.403572311
0.164741	-0.38051	0.649786	0.398344786
0.187022	-0.33808	0.628149	0.384417233
0.18782	-0.33656	0.627375	0.383918713
0.108703	-0.48721	0.704203	0.433373604
0.154508	-0.39999	0.659724	0.404741786
0.16965	-0.37116	0.64502	0.395276748
0.222641	-0.27026	-0.40644	0.299778637
0.237877	-0.24124	-0.42123	0.300118392
0.253314	-0.21185	-0.43623	0.300462607
0.248167	-0.22165	-0.43123	0.300347831
0.226787	-0.26236	-0.41047	0.299871096
0.252509	-0.21338	-0.43544	0.300444652
0.250653	-0.21692	-0.43364	0.300403274
0.259728	-0.19963	-0.44245	0.30060563
0.222778	-0.26999	-0.40657	0.2997817
0.256229	-0.2063	-0.43906	0.300527611
0.242438	-0.23256	-0.42566	0.300220083
0.252624	-0.21316	-0.43556	0.300447227
0.253018	-0.21241	-0.43594	0.300456004
0.239448	-0.23825	-0.42276	0.300153412
0.259123	-0.20079	-0.44187	0.300592129
0.247614	-0.2227	-0.43069	0.300335493
0.246587	-0.22466	-0.42969	0.300312605
0.256145	-0.20646	-0.43897	0.30052572

0.255837	-0.20704	-0.43868	0.300518874
0.249409	-0.21929	-0.43243	0.300375519
0.261211	-0.19681	-0.44389	0.300638688
0.242176	-0.23306	-0.42541	0.300214237
0.229492	-0.25721	-0.41309	0.299931401
0.248209	-0.22157	-0.43127	0.300348766
0.26097	-0.19727	-0.44366	0.300633312
0.254258	-0.21005	-0.43714	0.300483653
0.258828	-0.20135	-0.44158	0.300585552
0.252668	-0.21308	-0.4356	0.300448204
0.253476	-0.21154	-0.43638	0.300466208
0.234591	-0.2475	-0.41804	0.30004512
0.24157	-0.23421	-0.42482	0.300200724
0.235453	-0.24586	-0.41888	0.300064333
0.245239	-0.22723	-0.42838	0.30028254
0.256668	-0.20546	-0.43948	0.300537386
0.246456	-0.22491	-0.42956	0.30030967
0.25614	-0.20647	-0.43897	0.300525629
0.244992	-0.22769	-0.42814	0.300277042
0.230308	-0.25566	-0.41388	0.299949604
0.241352	-0.23463	-0.42461	0.300195863
0.252774	-0.21288	-0.4357	0.300450559
0.243031	-0.23143	-0.42624	0.300233317
0.230565	-0.25517	-0.41413	0.299955329
0.236291	-0.24426	-0.41969	0.300083025
0.249968	-0.21822	-0.43298	0.300388002
0.254634	-0.20933	-0.43751	0.300492049
0.243959	-0.22966	-0.42714	0.300254002
0.246834	-0.22419	-0.42993	0.300318107
0.266345	-0.18704	-0.44888	0.300753172
0.238846	-0.2394	-0.42218	0.30013999
0.264874	-0.18984	-0.44745	0.300720363
0.227998	-0.26006	-0.41164	0.299898086

0.229365	-0.25745	-0.41297	0.299928571
0.262623	-0.19412	-0.44526	0.300670177
0.25611	-0.20652	-0.43894	0.300524947
0.242812	-0.23185	-0.42603	0.300228415
0.247824	-0.2223	-0.43089	0.300340177
0.26001	-0.1991	-0.44273	0.300611911
0.243993	-0.2296	-0.42717	0.300254768
0.245228	-0.22725	-0.42837	0.300282299
0.248491	-0.22103	-0.43154	0.300355062
0.241112	-0.23508	-0.42438	0.300190512
0.238883	-0.23933	-0.42221	0.300140813
0.238595	-0.23988	-0.42193	0.300134388
0.244231	-0.22914	-0.4274	0.300260071
0.244742	-0.22817	-0.4279	0.30027147
0.233191	-0.25017	-0.41668	0.300013902
0.226682	-0.26256	-0.41036	0.299868754
0.241113	-0.23508	-0.42438	0.300190546
0.261813	-0.19567	-0.44448	0.300652111
0.252601	-0.21321	-0.43553	0.300446702
0.250881	-0.21648	-0.43386	0.300408357
0.254751	-0.20911	-0.43762	0.30049465
0.241274	-0.23478	-0.42453	0.300194125
0.245262	-0.22718	-0.42841	0.300283048
0.246128	-0.22553	-0.42925	0.300302367
0.22561	-0.2646	-0.40932	0.299844836
0.23331	-0.24994	-0.4168	0.300016544
0.235971	-0.24487	-0.41938	0.300075888
0.239847	-0.23749	-0.42315	0.300162319
0.257056	-0.20472	-0.43986	0.300546046
0.260251	-0.19864	-0.44296	0.300617283
0.253545	-0.21141	-0.43645	0.300467755
0.240146	-0.23692	-0.42344	0.300168977
0.236153	-0.24453	-0.41956	0.300079935

0.257224	-0.2044	-0.44002	0.300549782
0.23918	-0.23876	-0.4225	0.300147426
0.2591	-0.20083	-0.44184	0.300591618
0.263435	-0.19258	-0.44605	0.300688286
0.245103	-0.22748	-0.42825	0.300279502
0.255803	-0.20711	-0.43864	0.300518095
0.261298	-0.19665	-0.44398	0.300640643
0.230791	-0.25474	-0.41435	0.299960367
0.256343	-0.20608	-0.43917	0.30053015
0.255523	-0.20764	-0.43837	0.300511863
0.246331	-0.22515	-0.42944	0.300306889
0.250193	-0.21779	-0.43319	0.300393014
0.254873	-0.20888	-0.43774	0.300497362
0.259875	-0.19936	-0.4426	0.300608896
0.250661	-0.2169	-0.43365	0.300403436
0.231215	-0.25393	-0.41477	0.299969835
0.239241	-0.23865	-0.42256	0.300148806
0.25107	-0.21612	-0.43405	0.300412566
0.230914	-0.2545	-0.41447	0.299963108
0.255532	-0.20762	-0.43838	0.300512073
0.251197	-0.21588	-0.43417	0.300415395
0.243819	-0.22993	-0.427	0.300250883
0.239436	-0.23828	-0.42275	0.300153139
0.253662	-0.21119	-0.43656	0.300470358
0.234679	-0.24733	-0.41813	0.300047072
-0.73627	0.807977	0.553665	0.699305237
-0.73365	0.812969	0.551119	0.699246779
-0.72972	0.820454	0.547301	0.699159119
-0.73281	0.814574	0.5503	0.699227982
-0.72669	0.826227	0.544357	0.69909152
-0.74006	0.800763	0.557343	0.699389713
-0.72633	0.826907	0.544011	0.699083558
-0.73208	0.815965	0.549591	0.699211694

-0.7294	0.821075	0.546985	0.699151852
-0.71648	0.845663	0.534446	0.698863919
-0.73234	0.815477	0.54984	0.699217406
-0.74226	0.796587	0.559473	0.699438614
-0.72285	0.833545	0.540626	0.699005826
-0.71221	0.853799	0.530296	0.698768642
-0.74107	0.79885	0.558319	0.699412115
-0.73983	0.801212	0.557114	0.699384447
-0.74236	0.796384	0.559577	0.699440992
-0.73517	0.810082	0.552591	0.699280581
-0.73375	0.812786	0.551212	0.699248913
-0.72637	0.826829	0.544051	0.699084475
-0.72893	0.821957	0.546535	0.699141518
-0.73215	0.815827	0.549661	0.699213305
-0.73952	0.801803	0.556813	0.699377528
-0.74571	0.790005	0.56283	0.699515693
-0.72379	0.831752	0.54154	0.699026817
-0.73158	0.816912	0.549108	0.699200602
-0.73247	0.815228	0.549966	0.699220317
-0.72731	0.825053	0.544956	0.699105269
-0.74207	0.796942	0.559292	0.699434454
-0.72909	0.821653	0.54669	0.69914508
-0.73131	0.817438	0.54884	0.699194441
-0.74519	0.791005	0.562319	0.699503976
-0.72995	0.820016	0.547525	0.699164246
-0.72588	0.827769	0.543571	0.699073461
-0.72777	0.824177	0.545403	0.699115524
-0.73774	0.805189	0.555086	0.699337885
-0.71794	0.842888	-0.46414	0.674989287
-0.72117	0.83673	-0.461	0.672967832
-0.69848	0.879941	-0.48304	0.687152794
-0.70948	0.858994	-0.47235	0.680276318
-0.70803	0.861751	-0.47376	0.681181452

-0.72356	0.832182	-0.45868	0.671474678
-0.72408	0.831201	-0.45818	0.671152789
-0.6925	-0.10867	0.511157	0.43744287
-0.69084	-0.10551	0.509546	0.435299436
-0.67643	-0.07807	0.495552	0.416684072
-0.6751	-0.07554	0.494259	0.414965035

Appendix D: Error Computation for Purelin – Tansig activation parameters

Va Error	Ps Error	Rr Error	MAE
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06

0.001464217	0.004996062	-0.002799737	0.003086672
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
0.000941424	0.003212417	-0.001800282	0.001984708
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.98E-07	2.54E-06	-1.65E-06	1.60E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
8.07E-06	2.80E-05	-1.59E-05	1.73E-05
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06

5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
0.000322569	0.001101034	-0.00061718	0.000680261
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
3.83E-06	1.36E-05	-7.83E-06	8.42E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
0.000885702	0.003022306	-0.001693754	0.001867254
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
5.85E-07	2.50E-06	-1.62E-06	1.57E-06
0.23129219	-0.21088569	0.557823974	0.333333951
0.23129219	-0.21088569	0.557823974	0.333333951
0.23129219	-0.21088569	0.557823974	0.333333951
0.23129219	-0.21088569	0.557823974	0.333333951
0.231292081	-0.210886062	0.557824183	0.333334109
0.23129219	-0.21088569	0.557823974	0.333333951
0.23129219	-0.21088569	0.557823974	0.333333951

0.23129219	-0.21088569	0.557823974	0.333333951
0.23129219	-0.21088569	0.557823974	0.333333951
0.231292189	-0.210885691	0.557823975	0.333333952
0.23129219	-0.21088569	0.557823974	0.333333951
0.23129219	-0.21088569	0.557823974	0.333333951
0.23129219	-0.21088569	0.557823974	0.333333951
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0.23129219	-0.21088569	0.557823974	0.333333951
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0.23129219	-0.21088569	0.557823974	0.333333951
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-0.76870781	-0.21088569	0.557823974	0.512472491
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-0.76870781	-0.21088569	0.557823974	0.512472491

Appendix E: Error Computation for Purelin – Logsig activation parameters

Va Error	Ps Error	Rr Error	MAE
0.000570888	0.00967743	-0.0086481	0.006298806
0.000570888	0.00967743	-0.0086481	0.006298806
0.000570888	0.00967743	-0.0086481	0.006298806
0.000570888	0.00967743	-0.0086481	0.006298806
0.000570888	0.00967743	-0.0086481	0.006298806
0.000570888	0.00967743	-0.0086481	0.006298806
0.000570888	0.00967743	-0.0086481	0.006298806
0.000570888	0.00967743	-0.0086481	0.006298806
0.000570888	0.00967743	-0.0086481	0.006298806
0.000570889	0.009677435	-0.008648103	0.006298809
0.000570888	0.00967743	-0.0086481	0.006298806
0.000570888	0.00967743	-0.0086481	0.006298806
0.000570888	0.00967743	-0.0086481	0.006298806
0.000570888	0.00967743	-0.0086481	0.006298806
0.000570888	0.00967743	-0.0086481	0.006298806
0.001376396	0.012936861	-0.010452407	0.008255221
0.000570888	0.00967743	-0.0086481	0.006298806
0.000570888	0.00967743	-0.0086481	0.006298806
0.000570888	0.00967743	-0.0086481	0.006298806
0.000570888	0.00967743	-0.0086481	0.006298806
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0.000570888	0.00967743	-0.0086481	0.006298806
0.000570888	0.00967743	-0.0086481	0.006298806
0.000570888	0.00967743	-0.0086481	0.006298806
0.000570888	0.00967743	-0.0086481	0.006298806
0.000570888	0.00967743	-0.0086481	0.006298806
0.000571006	0.009677907	-0.008648365	0.006299093
0.000570888	0.00967743	-0.0086481	0.006298806
0.000570888	0.00967743	-0.0086481	0.006298806
0.000570888	0.00967743	-0.0086481	0.006298806
0.000570888	0.00967743	-0.0086481	0.006298806

0.187972677	0.767985085	-0.428420495	0.461459419
0.000570888	0.00967743	-0.0086481	0.006298806
0.000570893	0.009677448	-0.008648111	0.006298817
0.000570888	0.00967743	-0.0086481	0.006298806
0.000570888	0.00967743	-0.0086481	0.006298806
0.000570888	0.00967743	-0.0086481	0.006298806
0.000570888	0.00967743	-0.0086481	0.006298806
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0.000570888	0.00967743	-0.0086481	0.006298806
0.000570888	0.00967743	-0.0086481	0.006298806
0.195494727	0.798422513	-0.445269582	0.479728941
0.000570888	0.00967743	-0.008648101	0.006298806
0.000570888	0.00967743	-0.0086481	0.006298806
0.000570888	0.00967743	-0.0086481	0.006298806
0.000570888	0.00967743	-0.0086481	0.006298806
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0.000570888	0.00967743	-0.0086481	0.006298806
0.000583062	0.009726692	-0.00867537	0.006328375
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0.000570888	0.00967743	-0.0086481	0.006298806
0.000627012	0.009904532	-0.008773816	0.00643512
0.000570888	0.00967743	-0.0086481	0.006298806
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0.000570888	0.00967743	-0.0086481	0.006298806
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0.000570888	0.00967743	-0.0086481	0.006298806
0.000589729	0.009753668	-0.008690303	0.006344567
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0.002320387	0.016756648	-0.012566906	0.01054798
0.000570888	0.00967743	-0.008648101	0.006298806
0.000570888	0.00967743	-0.0086481	0.006298806

0.000570888	0.00967743	-0.0086481	0.006298806
0.000570888	0.00967743	-0.0086481	0.006298806
0.001282046	0.012555079	-0.010241066	0.008026064
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0.000965592	0.011274568	-0.00953222	0.00725746
0.000700941	0.010203681	-0.008939415	0.006614679
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0.109135298	0.448975391	-0.25182797	0.269979553
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0.198417992	-0.18974871	0.548182423	0.312116375
0.198417992	-0.189748709	0.548182423	0.312116375
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0.198417947	-0.189748888	0.548182522	0.312116453
0.198417992	-0.189748709	0.548182423	0.312116375
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0.198417992	-0.18974871	0.548182423	0.312116375
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0.198417992	-0.189748709	-0.451817577	0.279994759
-0.801582008	0.810251291	0.548182423	0.720005241
-0.801582008	0.810251291	0.548182423	0.720005241
-0.801582008	0.810251291	0.548182423	0.720005241
-0.801582008	0.810251291	0.548182423	0.720005241
-0.801582008	0.810251291	0.548182423	0.720005241
-0.801582008	0.810251291	0.548182423	0.720005241
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-0.801582008	0.810251291	0.548182423	0.720005241

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-0.801582008	0.810251291	0.548182423	0.720005241
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-0.801582008	0.810251291	0.548182423	0.720005241
-0.801582008	0.810251291	0.548182423	0.720005241
-0.801582008	0.810251291	0.548182423	0.720005241
-0.801582008	0.810251291	0.548182423	0.720005241
-0.801582008	0.810251291	0.548182423	0.720005241
-0.801582008	0.810251291	0.548182423	0.720005241
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-0.801582008	0.810251291	0.548182423	0.720005241
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-0.801582008	0.810251291	0.548182423	0.720005241
-0.801582008	0.810251291	0.548182423	0.720005241
-0.801582008	0.810251291	0.548182423	0.720005241
-0.801582008	0.810251291	0.548182423	0.720005241
-0.801582008	0.810251291	0.548182423	0.720005241
-0.801582008	0.810251291	0.548182423	0.720005241
-0.801582008	0.810251291	-0.451817577	0.687883625
-0.801582008	0.810251291	-0.451817577	0.687883625
-0.801582008	0.810251291	-0.451817577	0.687883625
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-0.801582008	0.810251291	-0.451817577	0.687883625

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-0.801582008	0.810251291	-0.451817577	0.687883625
-0.801582008	-0.189748709	0.548182423	0.513171047
-0.801582008	-0.189748709	0.548182423	0.513171047
-0.801582008	-0.189748709	0.548182423	0.513171047
-0.801582008	-0.189748709	0.548182423	0.513171047

Appendix F: Error Computation for Tansig – Purelin activation parameters

Va Error	Ps Error	Rr Error	MAE
4.48E-07	-6.13E-07	-3.05E-07	4.55E-07
-6.67E-08	-1.20E-08	-5.01E-07	1.93E-07
1.98E-07	-3.75E-07	1.43E-09	1.91E-07
3.70E-06	-3.69E-06	-4.04E-06	3.81E-06
1.36E-06	-1.48E-06	-1.40E-06	1.41E-06
9.15E-07	-1.03E-06	1.12E-07	6.85E-07
6.38E-07	-6.80E-07	-1.22E-06	8.45E-07
-1.89E-07	1.07E-07	-2.51E-07	1.82E-07
1.13E-06	-1.26E-06	-1.13E-06	1.18E-06
1.06E-07	-2.88E-07	1.14E-07	1.69E-07
-6.78E-07	5.48E-07	-1.38E-07	4.55E-07
1.71E-07	-3.49E-07	3.47E-08	1.85E-07
3.54E-06	-3.53E-06	-3.79E-06	3.62E-06
9.34E-07	-1.08E-06	-1.25E-06	1.09E-06
8.15E-07	-9.62E-07	-7.49E-07	8.42E-07
-2.92E-06	4.86E-06	1.36E-06	3.05E-06
1.53E-06	-1.64E-06	-1.60E-06	1.59E-06
-2.45E-06	2.26E-06	2.89E-06	2.54E-06
9.55E-08	-2.78E-07	1.27E-07	1.67E-07
8.39E-08	-2.67E-07	1.41E-07	1.64E-07
8.56E-08	-2.68E-07	1.39E-07	1.64E-07
8.59E-08	-2.68E-07	1.39E-07	1.64E-07
6.11E-07	-7.67E-07	-5.01E-07	6.26E-07
4.84E-07	-6.47E-07	-3.47E-07	4.93E-07
-2.13E-06	1.95E-06	2.25E-06	2.11E-06
-2.41E-06	2.17E-06	3.25E-06	2.61E-06
-2.21E-08	-1.92E-07	-8.32E-08	9.92E-08
3.31E-06	-3.32E-06	-3.64E-06	3.43E-06
1.17E-07	-2.98E-07	1.01E-07	1.72E-07
8.88E-08	-2.71E-07	1.35E-07	1.65E-07
1.68E-07	-2.39E-07	-8.80E-07	4.29E-07

-1.64E-06	6.24E-06	-3.17E-06	3.68E-06
-3.30E-07	1.27E-07	1.44E-07	2.00E-07
4.56E-06	-4.65E-06	-6.00E-06	5.07E-06
-1.38E-06	1.25E-06	1.60E-06	1.41E-06
3.37E-06	-3.38E-06	-3.62E-06	3.45E-06
-3.40E-06	3.14E-06	3.96E-06	3.50E-06
8.28E-08	-2.66E-07	1.43E-07	1.64E-07
-1.06E-06	8.31E-07	1.10E-06	9.98E-07
3.38E-07	-4.10E-07	-1.30E-06	6.84E-07
-2.50E-06	2.30E-06	2.77E-06	2.53E-06
-1.71E-06	1.46E-06	2.19E-06	1.79E-06
7.27E-07	0.394089595	-0.394092383	0.262727569
2.93E-07	-4.65E-07	-1.14E-07	2.90E-07
-6.20E-07	5.19E-07	3.82E-07	5.07E-07
-8.80E-07	7.73E-07	9.78E-07	8.77E-07
5.35E-07	-6.95E-07	-4.10E-07	5.47E-07
-6.18E-07	5.22E-07	5.42E-07	5.61E-07
1.26E-07	-3.07E-07	8.94E-08	1.74E-07
3.37E-06	-3.42E-06	-3.04E-06	3.28E-06
1.42E-07	-3.21E-07	7.04E-08	1.78E-07
9.50E-07	-1.09E-06	-9.08E-07	9.83E-07
1.32E-07	-3.13E-07	8.16E-08	1.76E-07
4.89E-06	-4.95E-06	-6.50E-06	5.44E-06
-3.47E-06	3.19E-06	4.40E-06	3.69E-06
2.46E-06	-2.52E-06	-2.68E-06	2.56E-06
1.90E-07	-3.67E-07	1.10E-08	1.90E-07
-2.58E-06	2.37E-06	2.91E-06	2.62E-06
-1.74E-06	1.52E-06	2.18E-06	1.81E-06
2.09E-07	-2.87E-07	-1.13E-06	5.41E-07
8.35E-08	-2.66E-07	1.42E-07	1.64E-07
-1.27E-06	1.11E-06	5.39E-07	9.70E-07
1.51E-07	-3.03E-07	-5.04E-07	3.19E-07
2.78E-07	-4.64E-07	-5.25E-07	4.22E-07

7.90E-07	-9.37E-07	-7.18E-07	8.15E-07
1.38E-07	-3.18E-07	7.46E-08	1.77E-07
9.71E-08	-1.37E-07	-1.75E-08	8.37E-08
-9.59E-07	8.44E-07	9.57E-07	9.20E-07
9.14E-08	-2.74E-07	1.32E-07	1.66E-07
2.50E-07	-4.24E-07	-6.22E-08	2.45E-07
3.28E-07	-4.99E-07	-1.58E-07	3.28E-07
1.39E-07	-3.01E-07	2.25E-07	2.22E-07
-3.91E-07	3.02E-07	1.05E-07	2.66E-07
1.07E-05	-1.06E-05	-1.43E-05	1.18E-05
1.67E-07	-3.46E-07	3.88E-08	1.84E-07
3.01E-06	-3.00E-06	-2.81E-06	2.94E-06
9.13E-08	3.93E-06	-4.07E-06	2.70E-06
6.66E-06	-6.64E-06	-8.92E-06	7.41E-06
3.44E-07	-4.17E-07	-1.32E-06	6.92E-07
2.69E-06	-2.74E-06	-2.95E-06	2.79E-06
3.04E-06	-3.07E-06	-3.37E-06	3.16E-06
1.58E-07	-3.37E-07	5.03E-08	1.82E-07
1.97E-06	-2.06E-06	-2.12E-06	2.05E-06
4.06E-07	-5.73E-07	-2.53E-07	4.11E-07
8.63E-08	-2.69E-07	1.38E-07	1.64E-07
-2.35E-06	2.15E-06	3.07E-06	2.52E-06
3.70E-07	-5.38E-07	-2.08E-07	3.72E-07
5.03E-07	0.00453675	-0.004537789	0.003025014
9.24E-08	-2.75E-07	1.31E-07	1.66E-07
1.86E-06	-1.96E-06	-2.00E-06	1.94E-06
2.43E-07	1.18E-07	-2.14E-06	8.33E-07
3.47E-07	7.48E-10	-2.68E-06	1.01E-06
1.53E-06	-3.65E-06	-4.67E-07	1.88E-06
1.47E-06	-1.15E-06	-2.81E-06	1.81E-06
1.11E-05	-0.14996737	0.149940832	0.099973107
1.47E-06	-1.16E-06	-2.82E-06	1.81E-06
-6.89E-07	9.83E-07	-8.91E-07	8.54E-07

-5.26E-07	8.28E-07	-1.65E-06	1.00E-06
-4.93E-07	7.97E-07	-1.69E-06	9.92E-07
9.66E-07	-7.48E-06	3.50E-06	3.98E-06
1.48E-06	-1.17E-06	-2.83E-06	1.83E-06
-9.90E-07	1.29E-06	-5.57E-07	9.45E-07
-5.66E-07	8.66E-07	-1.60E-06	1.01E-06
-2.69E-07	5.84E-07	-1.96E-06	9.37E-07
1.49E-06	-1.17E-06	-2.84E-06	1.83E-06
1.13E-06	-7.33E-07	-3.46E-06	1.77E-06
9.84E-07	-5.98E-07	4.87E-05	1.68E-05
-4.58E-07	7.62E-07	-1.71E-06	9.77E-07
1.59E-06	-1.41E-06	-2.83E-06	1.95E-06
4.03E-07	-5.37E-08	-2.76E-06	1.07E-06
-1.19E-06	1.39E-06	1.51E-07	9.12E-07
1.57E-06	-1.26E-06	-2.95E-06	1.92E-06
6.53E-06	-6.13E-06	-1.01E-05	7.60E-06
-3.44E-06	3.61E-06	2.72E-06	3.26E-06
-1.68E-06	1.95E-06	6.33E-07	1.42E-06
1.09E-06	-7.01E-07	-3.52E-06	1.77E-06
3.06E-07	4.49E-08	-2.24E-06	8.64E-07
1.35E-05	-1.29E-05	-1.96E-05	1.53E-05
1.49E-06	-1.17E-06	-2.84E-06	1.83E-06
1.51E-06	-1.20E-06	-2.87E-06	1.86E-06
4.56E-06	-4.21E-06	-7.47E-06	5.42E-06
-5.08E-06	5.02E-06	0.996195333	0.332068476
-3.28E-06	3.45E-06	2.67E-06	3.13E-06
1.20E-06	-0.206471935	0.20646872	0.137647285
-4.97E-07	8.01E-07	-1.68E-06	9.93E-07
-8.05E-07	1.00E-06	-5.13E-07	7.74E-07
-1.25E-06	1.53E-06	-2.27E-07	1.00E-06
1.50E-06	-1.19E-06	-2.86E-06	1.85E-06
-3.10E-06	3.24E-06	2.39E-06	2.91E-06
1.48E-06	-1.16E-06	-2.83E-06	1.82E-06

1.53E-06	-1.22E-06	-2.90E-06	1.88E-06
7.98E-06	-7.54E-06	-1.20E-05	9.17E-06
1.50E-06	-1.19E-06	-2.85E-06	1.85E-06
8.97E-07	-5.10E-07	-3.10E-06	1.50E-06
-2.59E-06	2.80E-06	1.83E-06	2.40E-06
-1.81E-06	2.07E-06	5.82E-07	1.48E-06
1.46E-06	-1.15E-06	-2.81E-06	1.81E-06
1.47E-06	-1.16E-06	-2.82E-06	1.82E-06
1.20E-05	-1.14E-05	-1.74E-05	1.36E-05
8.47E-07	-4.73E-07	-3.25E-06	1.52E-06
6.83E-07	-3.18E-07	-3.08E-06	1.36E-06
-5.78E-07	8.78E-07	-1.58E-06	1.01E-06
1.47E-06	-1.16E-06	-2.82E-06	1.82E-06
-3.35E-06	3.52E-06	2.69E-06	3.19E-06
7.80E-07	-4.08E-07	-3.15E-06	1.45E-06
3.39E-06	-3.28E-06	-1.70E-05	7.90E-06
-1.35E-06	1.47E-06	2.17E-06	1.67E-06
-2.80E-06	2.84E-06	3.73E-06	3.12E-06
-5.58E-06	5.49E-06	7.89E-06	6.32E-06
-1.49E-06	1.61E-06	2.32E-06	1.81E-06
-6.06E-06	5.91E-06	8.53E-06	6.83E-06
-3.79E-06	3.69E-06	5.60E-06	4.36E-06
-7.80E-07	8.27E-07	2.53E-06	1.38E-06
5.96E-06	-5.92E-06	-1.43E-05	8.74E-06
-3.49E-06	3.51E-06	5.11E-06	4.04E-06
-2.94E-06	2.97E-06	3.90E-06	3.27E-06
-1.40E-06	1.51E-06	2.11E-06	1.67E-06
-5.16E-06	5.34E-06	4.97E-06	5.16E-06
-4.63E-06	4.59E-06	-3.97E-05	1.63E-05
-2.70E-06	2.74E-06	3.61E-06	3.02E-06
-1.31E-06	1.43E-06	2.10E-06	1.62E-06
6.89E-06	-6.70E-06	-8.37E-06	7.32E-06
-1.98E-06	2.06E-06	2.76E-06	2.27E-06

-2.10E-06	2.17E-06	2.90E-06	2.39E-06
-1.88E-06	1.96E-06	2.63E-06	2.16E-06
-2.05E-06	2.14E-06	3.22E-06	2.47E-06
-2.92E-06	2.95E-06	7.07E-07	2.19E-06
7.37E-06	-7.20E-06	-9.07E-06	7.88E-06
-7.75E-07	8.23E-07	2.53E-06	1.37E-06
-1.37E-06	1.49E-06	2.15E-06	1.67E-06
-1.34E-06	1.46E-06	2.12E-06	1.64E-06
-3.01E-06	3.04E-06	3.98E-06	3.34E-06
-1.41E-06	1.52E-06	2.12E-06	1.68E-06
-2.62E-06	2.67E-06	3.52E-06	2.94E-06
-2.45E-06	2.50E-06	3.31E-06	2.75E-06
-5.89E-07	2.43E-07	6.07E-07	4.80E-07
-7.80E-07	8.27E-07	2.48E-06	1.36E-06
-2.26E-06	2.33E-06	3.09E-06	2.56E-06
9.65E-05	-9.65E-05	-9.42E-05	9.57E-05
-2.84E-06	2.89E-06	4.24E-06	3.32E-06
-7.81E-07	8.28E-07	2.53E-06	1.38E-06
-2.45E-06	2.51E-06	3.31E-06	2.76E-06
-2.88E-06	2.91E-06	3.83E-06	3.21E-06
-7.79E-07	8.26E-07	2.53E-06	1.38E-06
-2.76E-06	2.80E-06	3.68E-06	3.08E-06
-2.43E-06	2.49E-06	3.29E-06	2.73E-06
3.77E-06	-3.64E-06	-4.20E-06	3.87E-06
-6.22E-06	6.41E-06	-2.25E-05	1.17E-05
-7.78E-07	8.26E-07	2.53E-06	1.38E-06
-2.90E-06	2.93E-06	3.85E-06	3.23E-06
-1.40E-06	1.52E-06	2.25E-06	1.73E-06
-2.96E-06	2.99E-06	3.93E-06	3.29E-06
0.000102535	-0.000102505	-0.000101572	0.000102204
-2.75E-06	2.79E-06	3.67E-06	3.07E-06
3.10E-06	-3.03E-06	-2.29E-06	2.80E-06
5.79E-06	-5.76E-06	-7.24E-06	6.26E-06

-2.55E-06	2.60E-06	3.43E-06	2.86E-06
0.223977463	-0.223977395	-0.223977535	0.223977464
-1.64E-06	1.74E-06	2.57E-06	1.98E-06
-7.79E-07	8.26E-07	2.53E-06	1.38E-06
-1.22E-06	8.43E-07	1.38E-06	1.15E-06
-7.84E-07	8.33E-07	2.52E-06	1.38E-06
-1.55E-06	1.66E-06	2.45E-06	1.89E-06
-7.80E-07	8.27E-07	2.53E-06	1.38E-06
-1.74E-06	1.84E-06	2.73E-06	2.10E-06
-2.94E-06	2.97E-06	4.25E-07	2.11E-06
-7.73E-07	8.20E-07	2.52E-06	1.37E-06
-1.87E-06	1.83E-06	3.13E-06	2.28E-06
-1.76E-06	1.85E-06	2.50E-06	2.04E-06
-3.73E-06	3.74E-06	5.45E-06	4.31E-06
-4.23E-06	4.13E-06	6.20E-06	4.85E-06
5.83E-06	-5.80E-06	-7.29E-06	6.31E-06
-2.45E-06	2.51E-06	3.31E-06	2.76E-06
-2.05E-06	2.12E-06	2.84E-06	2.34E-06
-2.99E-06	3.01E-06	3.97E-06	3.32E-06
7.02E-06	-6.83E-06	-8.56E-06	7.47E-06
-1.43E-06	1.54E-06	2.15E-06	1.71E-06
-2.40E-06	2.46E-06	3.25E-06	2.70E-06
-1.64E-06	1.73E-06	2.36E-06	1.91E-06
-1.32E-06	1.44E-06	2.05E-06	1.61E-06
-5.62E-06	5.48E-06	8.00E-06	6.37E-06
-2.96E-06	2.99E-06	3.91E-06	3.28E-06
6.54E-06	-6.36E-06	-7.89E-06	6.93E-06
5.33E-06	-5.34E-06	-6.72E-06	5.80E-06
-2.32E-06	2.36E-06	3.25E-06	2.64E-06
-2.67E-06	2.71E-06	3.57E-06	2.99E-06
-2.53E-06	2.58E-06	3.41E-06	2.84E-06
-3.66E-06	3.68E-06	5.36E-06	4.23E-06
-2.96E-06	2.99E-06	3.93E-06	3.29E-06

-7.80E-07	8.27E-07	2.53E-06	1.38E-06
-2.43E-06	2.49E-06	3.29E-06	2.74E-06
-7.66E-07	8.14E-07	2.51E-06	1.36E-06
-2.95E-06	2.98E-06	3.91E-06	3.28E-06
-7.74E-07	8.21E-07	2.52E-06	1.37E-06
-2.11E-06	2.20E-06	3.24E-06	2.52E-06
-1.39E-06	1.51E-06	2.18E-06	1.69E-06
-7.62E-07	8.10E-07	2.40E-06	1.33E-06
-1.45E-06	1.56E-06	2.29E-06	1.77E-06
-7.75E-07	8.22E-07	2.52E-06	1.37E-06
-1.37E-06	1.49E-06	2.19E-06	1.68E-06
-2.97E-06	2.99E-06	3.93E-06	3.30E-06
-2.66E-06	2.70E-06	3.56E-06	2.97E-06
-1.83E-06	1.92E-06	2.58E-06	2.11E-06
-2.73E-06	2.77E-06	3.64E-06	3.05E-06
-2.95E-06	2.98E-06	3.91E-06	3.28E-06
7.42E-06	-7.26E-06	-9.18E-06	7.96E-06
-7.79E-07	8.26E-07	2.53E-06	1.38E-06
-4.94E-06	4.89E-06	7.07E-06	5.64E-06
-1.87E-06	1.96E-06	2.63E-06	2.15E-06
-1.58E-06	1.18E-06	1.82E-06	1.53E-06
-2.93E-06	2.96E-06	3.89E-06	3.26E-06
-2.88E-06	2.92E-06	3.83E-06	3.21E-06
-1.49E-06	1.60E-06	2.37E-06	1.82E-06
-6.08E-06	5.95E-06	8.57E-06	6.87E-06
7.95E-06	-8.11E-06	-9.36E-06	8.47E-06
7.97E-06	-8.12E-06	-8.80E-06	8.30E-06
1.24E-05	-1.23E-05	-1.49E-05	1.32E-05
1.23E-05	-1.22E-05	-1.54E-05	1.33E-05
1.13E-05	-1.13E-05	-1.34E-05	1.20E-05
1.15E-05	-1.20E-05	0.00038168	0.000135072
1.10E-05	-1.10E-05	-1.35E-05	1.18E-05
1.19E-05	-1.18E-05	-1.49E-05	1.29E-05

1.11E-05	-1.11E-05	-1.40E-05	1.21E-05
1.11E-05	-1.11E-05	-1.40E-05	1.21E-05
-9.06E-05	9.06E-05	8.77E-05	8.97E-05
7.97E-06	-8.11E-06	-9.42E-06	8.50E-06
1.11E-05	-1.11E-05	-1.40E-05	1.21E-05
1.14E-05	-1.14E-05	-1.44E-05	1.24E-05
2.13E-05	-2.12E-05	-3.37E-06	1.53E-05
3.22E-06	-3.20E-06	-5.34E-06	3.92E-06
1.05E-05	-1.06E-05	-1.20E-05	1.10E-05
-4.45E-05	4.46E-05	4.16E-05	4.36E-05
1.12E-05	-1.12E-05	-1.41E-05	1.21E-05
1.22E-05	-1.21E-05	-1.53E-05	1.32E-05
1.17E-05	-1.16E-05	-1.47E-05	1.27E-05
-4.17E-05	4.17E-05	3.96E-05	4.10E-05
1.06E-05	-1.07E-05	1.71E-05	1.28E-05
-7.26E-05	7.27E-05	6.72E-05	7.08E-05
1.11E-05	-1.11E-05	8.69E-06	1.03E-05
1.11E-05	-1.11E-05	-1.40E-05	1.20E-05
1.14E-05	-1.14E-05	-1.44E-05	1.24E-05
1.11E-05	-1.11E-05	-1.35E-05	1.19E-05
1.30E-05	-1.30E-05	-1.44E-05	1.35E-05
1.11E-05	-1.11E-05	-1.40E-05	1.21E-05
1.24E-05	-1.24E-05	-1.54E-05	1.34E-05
1.87E-05	-1.85E-05	-2.33E-05	2.02E-05
1.11E-05	-1.11E-05	-1.40E-05	1.20E-05
1.11E-05	-1.11E-05	-1.40E-05	1.20E-05
1.14E-05	-1.14E-05	-1.43E-05	1.24E-05
1.82E-05	-1.84E-05	0.006130634	0.002055741
2.43E-06	-1.02E-05	1.69E-05	9.82E-06
2.54E-06	-1.03E-05	-7.51E-06	6.77E-06
-1.72E-06	1.37E-05	3.24E-06	6.22E-06
1.68E-06	-5.17E-06	1.39E-05	6.92E-06
1.70E-06	1.78E-05	-9.10E-06	9.54E-06

-1.32E-06	-6.63E-06	1.51E-06	3.15E-06
2.51E-06	-1.02E-05	-1.66E-05	9.77E-06
5.18E-07	-1.74E-05	1.62E-05	1.14E-05
-8.84E-08	5.31E-06	-5.23E-06	3.54E-06
1.57E-06	3.72E-06	-6.96E-06	4.08E-06
3.21E-07	4.90E-06	-5.60E-06	3.61E-06

Appendix G: Error Computation for Tansig – Tansig activation parameters

Va Error	Ps Error	Rr Error	MAE
0.209386362	0.003645407	0.001995776	0.071675848
0.20938636	0.00364543	0.001995762	0.071675851
0.209386362	0.003645398	0.001995782	0.071675847
0.209386362	0.003645397	0.001995782	0.071675847
0.209386362	0.003645399	0.001995781	0.071675847
0.209386359	0.003645442	0.001995754	0.071675852
0.209386363	0.003645395	0.001995783	0.071675847
0.209386362	0.003645395	0.001995783	0.071675847
0.209386362	0.003645405	0.001995777	0.071675848
0.209385728	0.00365458	0.00199015	0.071676819
0.209386359	0.003645451	0.001995749	0.071675853
0.209386362	0.003645403	0.001995779	0.071675848
0.209386363	0.003645394	0.001995784	0.071675847
0.209386361	0.003645416	0.001995771	0.071675849
0.209386362	0.003645404	0.001995778	0.071675848
0.209374549	0.003816338	0.001890929	0.071693939
0.209386362	0.0036454	0.001995781	0.071675847
0.209386358	0.003645465	0.001995741	0.071675854
0.209386363	0.003645393	0.001995784	0.071675847
0.209386363	0.003645393	0.001995785	0.071675847
0.209386363	0.003645392	0.001995785	0.071675847
0.209386363	0.003645393	0.001995784	0.071675847
0.209386363	0.003645393	0.001995785	0.071675847
0.209386362	0.003645401	0.00199578	0.071675848
0.209386353	0.003645537	0.001995696	0.071675862
0.209386362	0.003645408	0.001995775	0.071675848
0.209386175	0.003648111	0.001994118	0.071676134
0.209386362	0.003645397	0.001995782	0.071675847
0.209386362	0.003645403	0.001995778	0.071675848
0.209386363	0.003645392	0.001995785	0.071675847
0.209386363	0.003645395	0.001995784	0.071675847

0.202421128	0.104430215	-0.059824302	0.122225215
0.209386361	0.003645419	0.001995769	0.071675849
0.209386308	0.003646187	0.001995297	0.071675931
0.209386362	0.003645399	0.001995781	0.071675847
0.209386362	0.003645399	0.001995781	0.071675847
0.209386359	0.003645448	0.001995751	0.071675853
0.209386293	0.003646406	0.001995164	0.071675954
0.209386362	0.003645403	0.001995779	0.071675848
0.209386363	0.003645395	0.001995783	0.071675847
0.209386351	0.003645566	0.001995678	0.071675865
0.209386362	0.003645404	0.001995778	0.071675848
0.204570662	0.073327107	-0.040746064	0.106214611
0.209385747	0.0036543	0.001990321	0.071676789
0.209386363	0.003645393	0.001995785	0.071675847
0.209386362	0.0036454	0.00199578	0.071675847
0.209386361	0.003645412	0.001995773	0.071675849
0.209386362	0.003645398	0.001995781	0.071675847
0.209386363	0.003645393	0.001995785	0.071675847
0.209386362	0.003645402	0.001995779	0.071675848
0.209233729	0.005853958	0.00064108	0.071909589
0.209386362	0.003645398	0.001995782	0.071675847
0.209386363	0.003645393	0.001995785	0.071675847
0.209383637	0.003684827	0.001971597	0.07168002
0.209386362	0.003645404	0.001995778	0.071675848
0.209386363	0.003645393	0.001995785	0.071675847
0.209386363	0.003645394	0.001995784	0.071675847
0.209386362	0.003645401	0.00199578	0.071675848
0.209386361	0.003645411	0.001995774	0.071675849
0.209382678	0.003698709	0.001963081	0.071681489
0.209386363	0.003645392	0.001995785	0.071675847
0.208485329	0.016683071	-0.006001356	0.077056586
0.209386347	0.003645624	0.001995643	0.071675871
0.209386362	0.003645395	0.001995783	0.071675847

0.209386363	0.003645395	0.001995784	0.071675847
0.209386363	0.003645392	0.001995785	0.071675847
0.206697967	0.042545652	-0.021865123	0.090369581
0.209386363	0.003645394	0.001995784	0.071675847
0.209386363	0.003645394	0.001995784	0.071675847
0.209386363	0.003645393	0.001995785	0.071675847
0.209386363	0.003645394	0.001995784	0.071675847
0.20938636	0.003645427	0.001995764	0.07167585
0.209386363	0.003645394	0.001995784	0.071675847
0.209386358	0.003645467	0.001995739	0.071675855
0.209386363	0.003645393	0.001995785	0.071675847
0.209386362	0.003645404	0.001995778	0.071675848
0.207899967	0.02515308	-0.011196748	0.081416598
0.20938267	0.00369883	0.001963007	0.071681502
0.209386363	0.003645394	0.001995784	0.071675847
0.209386363	0.003645393	0.001995785	0.071675847
0.209386362	0.0036454	0.00199578	0.071675847
0.209386363	0.003645393	0.001995785	0.071675847
0.209386363	0.003645392	0.001995785	0.071675847
0.209386362	0.003645409	0.001995775	0.071675848
0.209386363	0.003645393	0.001995785	0.071675847
0.209386362	0.003645406	0.001995777	0.071675848
0.209386361	0.00364541	0.001995774	0.071675849
0.205497867	0.059910745	-0.032516643	0.099308418
0.209380002	0.003737436	0.001939327	0.071685588
0.209386362	0.003645397	0.001995782	0.071675847
0.126744453	0.199448606	0.268505795	0.198232951
0.125737752	0.214015274	0.259570792	0.199774606
0.130150012	0.150171207	0.298731904	0.193017708
0.126904068	0.197139032	0.269922457	0.197988519
0.134958684	0.080591201	0.341411367	0.18565375
0.127450714	0.189229236	0.274774223	0.197151391
0.144155935	-0.052490222	0.423041764	0.206562641

0.126327801	0.205477439	0.264807788	0.198871009
0.126138281	0.208219738	0.263125698	0.199161239
0.134777222	0.083216899	0.339800798	0.18593164
0.135647994	0.070617095	0.347529353	0.184598147
0.125666172	0.215051015	0.258935482	0.199884223
0.130762647	0.141306575	0.304169354	0.192079525
0.128052193	0.180526016	0.280112663	0.196230291
0.127532682	0.188043183	0.275501732	0.197025865
0.130098168	0.150921376	0.298271761	0.193097102
0.139403427	0.016277128	0.380860774	0.17884711
0.125816336	0.212878187	0.260268266	0.199654263
0.12855275	0.173283107	0.284555368	0.195463742
0.127176049	0.193203545	0.272336434	0.197572009
0.133080646	0.107765839	0.3247428	0.188529762
0.127822836	0.183844746	0.278076998	0.196581526
0.129633771	0.157641061	0.294149994	0.193808275
0.13783148	0.039022717	0.366908929	0.181254375
0.128359836	0.17607452	0.282843152	0.195759169
0.127411072	0.189802839	0.274422382	0.197212098
0.126342912	0.205258795	0.264941901	0.198847869
0.125575942	0.216356605	0.25813465	0.200022399
0.126465174	0.2034897	0.266027041	0.198660638
0.12888041	0.168541964	0.287463524	0.194961966
0.126786871	0.198834832	0.268882276	0.198167993
0.14364428	-0.045086733	0.418500561	0.202410525
0.126312003	0.20570603	0.264667573	0.198895202
0.129948394	0.153088564	0.296942436	0.193326465
0.132039943	0.122824485	0.315506025	0.190123484
0.126675659	0.200444034	0.267895212	0.198338302
0.125575082	0.216369057	0.258127012	0.200023717
0.129042091	0.166202486	0.288898528	0.194714369
0.127919145	0.182451184	0.27893179	0.19643404
0.134518276	0.086963772	0.337502515	0.186328188

0.126461547	0.203542172	0.265994856	0.198666192
0.139856954	0.009714722	0.384886068	0.178152581
0.127759751	0.184757563	0.277517088	0.196678134
0.126839798	0.198068998	0.269352029	0.198086941
0.126751394	0.199348174	0.268567399	0.198222322
0.130496017	0.145164626	0.301802875	0.19248784
0.127371457	0.190376057	0.274070777	0.197272764
0.129092135	0.165478368	0.289342693	0.194637732
0.125642873	0.215388135	0.258728697	0.199919902
0.126042333	0.209608079	0.262274108	0.199308173
0.128754599	0.170362421	0.286346879	0.195154633
0.130212105	0.149272752	0.299283005	0.19292262
0.127221881	0.192540377	0.272743212	0.197501823
0.127304964	0.191338188	0.273480619	0.19737459
0.125637991	0.215458786	0.258685361	0.199927379
0.145396815	-0.070445375	-0.565944781	0.260595657
0.147482858	-0.100629782	-0.547430062	0.265180901
0.159132728	-0.269199842	-0.4440314	0.29078799
0.162017495	-0.310941543	-0.418427589	0.297128876
0.142614511	-0.030186283	-0.59063918	0.254479991
0.172804989	-0.467033294	-0.322682958	0.320840414
0.171745946	-0.451709257	-0.332082522	0.318512575
0.167553384	-0.391044169	-0.36929369	0.309297081
0.146052448	-0.079932184	-0.560125697	0.262036776
0.169060273	-0.412848395	-0.355919264	0.312609311
0.157408809	-0.244255266	-0.459332076	0.286998717
0.157079197	-0.239485872	-0.462257559	0.286274209
0.157655589	-0.247826097	-0.457141775	0.287541154
0.147743721	-0.104404386	-0.54511477	0.265754292
0.172088604	-0.456667414	-0.329041253	0.319265757
0.160469447	-0.288541768	-0.432167317	0.293726178
0.168678836	-0.407329118	-0.359304716	0.31177089
0.16254279	-0.318542405	-0.41376532	0.298283505

0.162709345	-0.320952397	-0.412287063	0.298649601
0.15705102	-0.239078164	-0.462507643	0.286212275
0.167177381	-0.385603526	-0.372630909	0.308470606
0.149810331	-0.134307598	-0.526772532	0.27029682
0.151406605	-0.1574052	-0.512604766	0.273805524
0.158158013	-0.255096009	-0.452682506	0.288645509
0.16448055	-0.346581195	-0.396566694	0.302542813
0.162868547	-0.323256004	-0.41087406	0.298999537
0.165408955	-0.360014936	-0.388326614	0.304583502
0.158579991	-0.261201912	-0.448937226	0.289573043
0.163239872	-0.328628971	-0.407578353	0.299815732
0.150301752	-0.141418316	-0.522410911	0.271376993
0.163826544	-0.337117932	-0.402371336	0.301105271
0.147530993	-0.101326281	-0.547002839	0.265286704
0.158148203	-0.254954062	-0.452769575	0.288623946
0.173275185	-0.473836886	-0.318509725	0.321873932
0.156990897	-0.238208204	-0.463041264	0.286080122
0.166650968	-0.37798649	-0.377303099	0.307313519
0.151137648	-0.153513472	-0.514991901	0.27321434
0.152056716	-0.166812115	-0.506834688	0.275234506
0.151239032	-0.154980465	-0.514092066	0.273437188
0.168583688	-0.405952348	-0.360149209	0.311561748
0.155594473	-0.218002368	-0.475435259	0.2830107
0.151933674	-0.165031732	-0.507926751	0.274964053
0.148939807	-0.121711392	-0.534498879	0.268383359
0.166695665	-0.378633241	-0.37690639	0.307411766
0.172269111	-0.459279306	-0.327439153	0.319662523
0.157302795	-0.242721278	-0.460273004	0.286765692
0.165756	-0.365036574	-0.385246408	0.305346327
0.172137401	-0.457373492	-0.328608154	0.319373016
0.154075008	-0.196016178	-0.488921299	0.279670828
0.16607005	-0.369580784	-0.382459048	0.306036628
0.150262795	-0.140854618	-0.522756676	0.271291363

0.148495615	-0.11528407	-0.538441314	0.267407
0.167471684	-0.389861994	-0.370018821	0.3091175
0.15888734	-0.265649154	-0.446209346	0.290248613
0.151462715	-0.158217097	-0.512106759	0.273928857
0.170586637	-0.434934412	-0.342371992	0.315964347
0.164954151	-0.353434058	-0.392363238	0.303583816
0.147886875	-0.106475782	-0.543844202	0.266068953
0.162584429	-0.319144911	-0.413395751	0.29837503
0.154411565	-0.200886056	-0.48593418	0.2804106
0.149821977	-0.13447612	-0.526669162	0.27032242
0.158006271	-0.252900361	-0.454029288	0.288311973
0.159214747	-0.270386641	-0.443303433	0.290968274
0.152965554	-0.179962718	-0.498768281	0.277232184
0.160031846	-0.282209813	-0.436051255	0.292764305
0.153447583	-0.186937529	-0.494490023	0.278291712
0.14914391	-0.124664693	-0.532687363	0.268831989
0.148300889	-0.112466437	-0.540169613	0.26697898
0.163316071	-0.329731545	-0.406902049	0.299983222
0.15701972	-0.238625259	-0.462785448	0.286143476
0.173260756	-0.4736281	-0.318637791	0.321842216
0.163360213	-0.330370265	-0.406510266	0.300080248
0.150969789	-0.151084611	-0.516481732	0.272845377
0.153689567	-0.190438967	-0.492342287	0.278823607
0.150208898	-0.140074752	-0.523235035	0.271172895
0.146491481	-0.086284856	-0.556229051	0.263001796
0.15156448	-0.159689612	-0.511203538	0.274152543
0.157396267	-0.244073788	-0.459443392	0.286971149
0.161829997	-0.308228512	-0.420091727	0.296716745
0.17440969	-0.490252822	-0.308440405	0.324367639
0.167343012	-0.388000152	-0.37116085	0.308834671
0.159612556	-0.276142805	-0.439772678	0.29184268
0.155336092	-0.214263675	-0.477728524	0.282442764
0.154696741	-0.20501247	-0.483403092	0.281037434

0.15701961	-0.238623679	-0.462786417	0.286143236
0.152446664	-0.172454539	-0.503373699	0.276091634
0.164793361	-0.351107484	-0.393790328	0.303230391
0.17217017	-0.45784765	-0.328317312	0.319445044
0.158984329	-0.26705255	-0.445348521	0.2904618
0.163069641	-0.326165775	-0.409089245	0.299441554
0.163221804	-0.328367523	-0.407738722	0.299776016
0.149844693	-0.13480481	-0.526467549	0.27037235
0.159165296	-0.269671093	-0.443742341	0.290859577
0.16086408	-0.294251974	-0.428664752	0.294593602
0.156209217	-0.226897528	-0.469979084	0.284361943
0.161789134	-0.307637223	-0.420454416	0.296626924
0.169814234	-0.423757979	-0.349227469	0.314266561
0.163061695	-0.326050794	-0.409159773	0.299424087
0.160202563	-0.284680036	-0.434536053	0.293139551
0.153058568	-0.181308601	-0.497942733	0.277436634
0.161000994	-0.296233078	-0.427449569	0.294894547
0.161351613	-0.30130644	-0.424337635	0.295665229
0.148363649	-0.113374565	-0.53961258	0.267116931
0.162503396	-0.317972378	-0.414114967	0.298196914
0.174164625	-0.486706803	-0.310615486	0.323828971
0.15383312	-0.192516136	-0.491068179	0.279139145
0.161441809	-0.302611538	-0.423537105	0.295863484
0.166626761	-0.377636219	-0.37751795	0.30726031
0.15083203	-0.149091277	-0.517704417	0.272542575
-0.821010678	0.443481295	0.732206218	0.665566063
-0.817812775	0.397208614	0.760589273	0.658536887
-0.829953203	0.572876899	0.652836653	0.685222252
-0.827241963	0.53364609	0.676900316	0.67926279
-0.817364834	0.390727041	0.764564984	0.657552286
-0.817359171	0.390645101	0.764615245	0.657539839
-0.82227799	0.461818922	0.720958158	0.66835169
-0.826007841	0.515788723	0.687853791	0.676550118

-0.823014123	0.47247054	0.714424595	0.669969753
-0.823797096	0.483799921	0.707475302	0.671690773
-0.826911043	0.528857776	0.679837405	0.678535408
-0.824525192	0.494335249	0.70101307	0.67329117
-0.826476928	0.522576267	0.6836904	0.677581198
-0.824624359	0.495770154	0.700132918	0.673509144
-0.818817826	0.411751399	0.751668919	0.660746048
-0.827348702	0.535190566	0.675952955	0.679497407
-0.821233822	0.446710126	0.730225695	0.666056548
-0.8296753	0.568855734	0.655303183	0.684611406
-0.823232929	0.475636585	0.712482585	0.670450699
-0.83165932	0.5975639	0.637693971	0.688972397
-0.823934099	0.485782307	0.706259332	0.671991913
-0.829976908	0.57321991	0.652626254	0.685274358
-0.818644588	0.409244703	0.753206494	0.660365262
-0.823247934	0.475853708	0.712349404	0.670483682
-0.817547237	0.39336637	0.762946055	0.657953221
-0.824622953	0.495749818	0.700145392	0.673506054
-0.822393375	0.463488499	0.719934061	0.668605312
-0.817023336	0.385785681	0.767595949	0.656801656
-0.820595686	0.437476485	0.735889489	0.664653887
-0.820177783	0.431429563	0.739598592	0.663735313
-0.82627403	0.519640389	0.685491229	0.677135216
-0.822980964	0.471990739	0.714718899	0.669896867
-0.826845361	0.527907374	0.680420369	0.678391035
-0.82874555	0.555402542	0.663555194	0.682567762
-0.828254279	0.548293988	0.667915488	0.681487918
-0.815542923	0.364364549	0.78073539	0.653547621
-0.817447649	0.391925353	-0.236170045	0.481847682
-0.817682486	0.395323369	-0.238254343	0.483753399
-0.809182767	0.272335041	-0.162814917	0.414777575
-0.819503507	0.421672987	-0.254416853	0.498531115
-0.820303059	0.433242262	-0.261513294	0.505019538

-0.808900058	0.268244323	-0.160305725	0.412483369
-0.813032786	0.328043636	-0.196985838	0.446020753
-0.842564686	-0.244638777	0.540903165	0.542702209
-0.860059409	0.008504523	0.385628388	0.418064107
-0.860774698	0.018854538	0.379279825	0.419636354
-0.870781427	0.163648849	0.290464896	0.441631724

Appendix H: Error Computation for Tansig – Logsig activation parameters

Va Error	Ps Error	Rr Error	MAE
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05
-1.95E-05	-6.59E-05	3.38E-05	3.97E-05
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05
-1.99E-05	-6.73E-05	3.46E-05	4.06E-05
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05

0.00158275	0.005541908	-0.002935025	0.003353228
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05
0.001635566	0.005726762	-0.003032889	0.003465072
-1.98E-05	-6.71E-05	3.45E-05	4.05E-05
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05
-1.99E-05	-6.74E-05	3.46E-05	4.06E-05
-1.60E-05	-5.38E-05	2.74E-05	3.24E-05
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-1.98E-05	-6.71E-05	3.45E-05	4.05E-05
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-1.99E-05	-6.74E-05	3.46E-05	4.06E-05

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-0.774834067	-0.21192015	0.582781688	0.523178635

Appendix I: Error Computation for Logsig – Purelin activation parameters

Va Error	Ps Error	Rr Error	MAE
0.111346546	-0.049899822	0.119788526	0.093678298
0.111763864	-0.020054182	0.100563696	0.077460581
0.112140904	0.006910815	0.083194409	0.067415376
0.112699034	0.046826955	0.057482747	0.072336245
0.111391194	-0.046706714	0.117731712	0.091943206
0.111040471	-0.071789555	0.133888622	0.105572883
0.112728707	0.048949151	0.056115752	0.07259787
0.112787214	0.053133414	0.053420492	0.073113707
0.112429169	0.027526885	0.069914733	0.069956929
0.111155601	-0.063555738	0.128584876	0.101098738
0.112438857	0.028219738	0.069468437	0.070042344
0.112186514	0.010172774	0.081093245	0.067817511
0.112682251	0.04562667	0.058255901	0.072188274
0.112991921	0.067773561	0.043990159	0.074918547
0.112778183	0.052487497	0.053836555	0.073034078
0.113850318	0.129164087	0.004445943	0.082486783
0.112565676	0.037289526	0.063626206	0.071160469
0.112586642	0.038788932	0.062660376	0.071345316
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-0.880241404	-0.448289679	0.732266169	0.686932418
-0.880292798	-0.451965231	0.734633746	0.688963925
-0.883467172	-0.678989006	0.880869294	0.814441824
-0.880787835	-0.487369134	0.757438887	0.708531952

Appendix J: Error Computation for Logsig – Tansig activation parameters

Va Error	Ps Error	Rr Error	MAE
0.14441586	0.005855613	0.053194377	0.06782195
0.144724929	0.013479861	0.047858152	0.068687647
0.144400101	0.005466866	0.053466462	0.06777781
0.144497936	0.00788029	0.051777302	0.068051843
0.144537531	0.008857043	0.051093671	0.068162748
0.145522832	0.03316288	0.034081972	0.070922562
0.144598343	0.01035717	0.050043729	0.068333081
0.14461623	0.010798422	0.049734896	0.068383183
0.144406151	0.005616101	0.053362012	0.067794755
0.145253535	0.026519732	0.038731523	0.070168263
0.144460347	0.006953036	0.052426289	0.067946557
0.144409698	0.005703591	0.053300777	0.067804689
0.144534725	0.008787825	0.051142116	0.068154889
0.147359542	0.078471628	0.002370299	0.076067156
0.144497057	0.007858618	0.05179247	0.068049382
0.149512678	0.131586099	-0.034804614	0.10530113
0.144417268	0.005890338	0.053170073	0.067825893
0.145669139	0.036772043	0.031555912	0.071332365
0.144352919	0.004302947	0.054281091	0.067645652
0.144374583	0.004837379	0.053907041	0.067706334
0.144353599	0.004319739	0.054269338	0.067647559
0.144361008	0.004502508	0.054141417	0.067668311
0.144381417	0.005005962	0.053789049	0.067725476
0.144458824	0.006915461	0.052452587	0.067942291
0.144913643	0.018135124	0.044599926	0.069216231
0.144947025	0.01895861	0.044023566	0.069309734
0.146650901	0.060990551	0.014605336	0.074082262
0.144467668	0.007133635	0.052299887	0.067967063
0.144372557	0.004787386	0.053942031	0.067700658
0.144370677	0.004741018	0.053974484	0.067695393
0.14447137	0.007224952	0.052235974	0.067977432

0.166550393	0.551879789	-0.328968914	0.349133032
0.145150474	0.02397738	0.04051092	0.069879591
0.146100159	0.047404619	0.024114154	0.072539644
0.144955702	0.019172662	0.043873751	0.069334038
0.144647157	0.011561334	0.049200933	0.068469808
0.14501068	0.020528884	0.042924529	0.069488031
0.1453486	0.028864843	0.037090176	0.07043454
0.145009603	0.020502312	0.042943126	0.069485014
0.144471926	0.007238658	0.052226381	0.067978988
0.144628884	0.011110569	0.049516424	0.068418626
0.14511614	0.023130424	0.041103706	0.069783423
0.148726224	0.112185534	-0.021226124	0.094045961
0.14638598	0.054455373	0.019179318	0.073340224
0.144570513	0.009670657	0.050524221	0.06825513
0.144940595	0.018800005	0.044134574	0.069291725
0.144483378	0.007521176	0.052028646	0.068011067
0.144946072	0.018935112	0.044040013	0.069307065
0.144368049	0.00467619	0.054019857	0.067688032
0.14484464	0.016432929	0.045791294	0.069022954
0.146555193	0.058629605	0.016257766	0.073814188
0.144461261	0.006975581	0.05241051	0.067949117
0.144373717	0.004816007	0.053921999	0.067703908
0.147765806	0.088493511	-0.004644035	0.080301117
0.145134391	0.023580633	0.040788604	0.069834543
0.144434212	0.006308336	0.052877515	0.067873355
0.144368581	0.004689304	0.054010679	0.067689521
0.144780388	0.014847938	0.046900633	0.068842986
0.146842639	0.065720441	0.011294878	0.074619319
0.144943886	0.018881193	0.044077751	0.069300943
0.144361105	0.004504888	0.054139752	0.067668582
0.164401889	0.498879567	-0.291873965	0.31838514
0.144472552	0.007254112	0.052215565	0.067980743
0.144951178	0.019061062	0.04395186	0.069321367

0.1444266	0.006120544	0.053008951	0.067852032
0.144372993	0.00479815	0.053934497	0.06770188
0.148474239	0.105969457	-0.016875481	0.090439726
0.144658549	0.011842374	0.049004232	0.068501719
0.144424732	0.006074479	0.053041192	0.067846801
0.144391407	0.005252405	0.053616563	0.067753459
0.144390948	0.005241077	0.053624492	0.067752172
0.144921087	0.018318764	0.044471396	0.069237082
0.144569	0.00963333	0.050550346	0.068250892
0.145993146	0.044764792	0.025961773	0.072239904
0.1443606	0.004492439	0.054148465	0.067667168
0.14483761	0.016259513	0.045912669	0.069003264
0.148405873	0.10428297	-0.015695105	0.089461316
0.147819691	0.089822765	-0.005574382	0.081072279
0.14447209	0.007242714	0.052223543	0.067979449
0.144467475	0.007128878	0.052303217	0.067966523
0.144451519	0.006735273	0.052578702	0.067921831
0.144379047	0.004947496	0.05382997	0.067718838
0.144411884	0.005757539	0.053263019	0.067810814
0.144509368	0.008162297	0.051579925	0.068083863
0.144352596	0.004294984	0.054286664	0.067644748
0.144923653	0.018382061	0.044427094	0.069244269
0.144465878	0.007089483	0.052330789	0.06796205
0.146693766	0.062047964	0.013865251	0.074202327
0.144724419	0.013467288	0.047866952	0.06868622
0.144490297	0.007691848	0.051909193	0.068030446
0.192542122	0.193054938	0.222271459	0.20262284
0.194165521	0.233101637	0.194242704	0.207169954
0.188180241	0.085454174	0.297581426	0.19040528
0.192996792	0.204270926	0.214421369	0.203896363
0.187541921	0.069707839	0.308602313	0.188617358
0.192969676	0.203602016	0.214889541	0.203820411
0.175829437	-0.219220758	0.510823952	0.301958049

0.194140703	0.23248943	0.194671188	0.207100441
0.194148402	0.232679355	0.19453826	0.207122006
0.165682083	-0.469540046	0.686022866	0.440414998
0.18285071	-0.04601698	0.38959832	0.206155336
0.194125094	0.232104384	0.194940683	0.20705672
0.187519458	0.069153705	0.308990153	0.188554439
0.191468535	0.166571229	0.240807455	0.19961574
0.191935665	0.178094601	0.232742226	0.200924164
0.186781913	0.050959628	0.32172422	0.186488587
0.178492981	-0.153515302	0.464836586	0.265614957
0.194130307	0.232232961	0.194850692	0.20707132
0.192035485	0.180557008	0.231018783	0.201203759
0.192953891	0.203212625	0.215162077	0.203776197
0.183181486	-0.037857248	0.383887309	0.201642014
0.192080245	0.181661166	0.230245981	0.201329131
0.188908271	0.103413537	0.285011635	0.192444481
0.179392011	-0.131337662	0.449314417	0.25334803
0.189791657	0.12520528	0.269759556	0.194918831
0.191046055	0.156149318	0.248101769	0.198432381
0.194151217	0.232748798	0.194489656	0.207129891
0.19417617	0.233364335	0.194058841	0.207199782
0.191400442	0.164891491	0.241983106	0.199425013
0.191028195	0.155708735	0.248410134	0.198382354
0.193073017	0.206151277	0.213105309	0.204109867
0.176178736	-0.210604106	0.504793142	0.297191995
0.193545227	0.217799956	0.204952378	0.20543252
0.192477477	0.191460258	0.223387579	0.202441772
0.184862636	0.003614081	0.354861452	0.181112723
0.193195682	0.209177242	0.210987431	0.204453451
0.194090471	0.231250268	0.19553848	0.20695974
0.190000717	0.130362459	0.266150037	0.195504404
0.191369686	0.164132789	0.242514123	0.199338866
0.183472581	-0.0306764	0.378861421	0.197670134

0.193374197	0.213580915	0.207905292	0.204953468
0.179388808	-0.13141666	0.449369708	0.253391725
0.192178151	0.184076356	0.228555585	0.201603364
0.191037732	0.155944003	0.248245469	0.198409068
0.192004672	0.179796884	0.231550795	0.20111745
0.186136704	0.035043341	0.332864057	0.184681367
0.193032475	0.205151173	0.213805283	0.20399631
0.187229173	0.061992824	0.314002066	0.187741354
0.194152859	0.232789295	0.194461312	0.207134489
0.19272239	0.197501874	0.219159041	0.203127768
0.188523429	0.093920102	0.291656108	0.191366546
0.186972886	0.055670629	0.318426982	0.187023499
0.188897785	0.103154867	0.285192679	0.19241511
0.19224375	0.185694573	0.227422992	0.201787105
0.194136751	0.232391935	0.194739426	0.207089371
0.176560313	-0.2011912	-0.501794968	0.29318216
0.174144865	-0.260776501	-0.46009111	0.298337492
0.172915061	-0.291113837	-0.438857954	0.300962284
0.17074616	-0.344617214	-0.401410846	0.305591407
0.176493784	-0.202832373	-0.500646308	0.293324155
0.168458301	-0.401055105	-0.361909866	0.310474424
0.16872305	-0.394524171	-0.366480878	0.309909366
0.169716605	-0.37001474	-0.383635072	0.307788806
0.176102263	-0.212490562	-0.493886524	0.294159783
0.168986223	-0.388032112	-0.371024681	0.309347672
0.171323866	-0.330366126	-0.411385207	0.3043584
0.17252327	-0.30077871	-0.432093493	0.301798491
0.172626016	-0.298244141	-0.433867442	0.301579199
0.176921335	-0.192285354	-0.508028185	0.292411625
0.169583173	-0.373306299	-0.381331304	0.308073592
0.170784557	-0.343670038	-0.402073776	0.305509457
0.169336609	-0.379388631	-0.377074269	0.308599836
0.171344144	-0.329865909	-0.41173531	0.304315121

0.171427398	-0.327812158	-0.413172735	0.30413743
0.172235276	-0.307883082	-0.42712113	0.302413162
0.16896842	-0.388471277	-0.370717309	0.309385669
0.174899535	-0.24215998	-0.473120846	0.296726787
0.174096797	-0.261962276	-0.459261183	0.298440086
0.172426471	-0.303166583	-0.430422216	0.30200509
0.171825882	-0.31798219	-0.420052747	0.303286939
0.170242061	-0.357052567	-0.39270732	0.306667316
0.169556506	-0.373964116	-0.380870897	0.308130506
0.171702765	-0.321019279	-0.417927082	0.303549709
0.171582328	-0.323990275	-0.415847677	0.30380676
0.17511891	-0.236748355	-0.476908452	0.296258572
0.170323108	-0.355053262	-0.394106637	0.306494336
0.177302918	-0.182872288	-0.514616407	0.291597204
0.172686055	-0.29676307	-0.434904046	0.301451057
0.167986505	-0.412693592	-0.353764068	0.311481388
0.171826211	-0.317974053	-0.420058442	0.303286235
0.170642267	-0.347180104	-0.399617075	0.305813148
0.17510606	-0.23706534	-0.476686593	0.296285998
0.174301009	-0.256924691	-0.462786999	0.298004233
0.175491839	-0.227548772	-0.483347257	0.295462622
0.170184876	-0.358463225	-0.391719998	0.306789366
0.173267736	-0.282413893	-0.444947061	0.300209563
0.17401864	-0.263890288	-0.457911765	0.298606897
0.174180097	-0.259907386	-0.460699405	0.298262296
0.170913709	-0.340484049	-0.404303655	0.305233805
0.168613742	-0.397220624	-0.364593626	0.310142664
0.171577859	-0.324100521	-0.415770516	0.303816298
0.169434889	-0.376964235	-0.378771109	0.308390077
0.168278382	-0.405493427	-0.358803476	0.310858428
0.173343606	-0.280542299	-0.446256993	0.300047633
0.172098557	-0.311255715	-0.424760618	0.302704963
0.174432533	-0.253680201	-0.465057822	0.297723519

0.176429134	-0.204427186	-0.499530095	0.293462138
0.170740759	-0.34475047	-0.40131758	0.305602936
0.174190154	-0.259659301	-0.46087304	0.298240832
0.175442223	-0.228772727	-0.482490608	0.295568519
0.168719717	-0.394606397	-0.366423327	0.309916481
0.169904764	-0.365373141	-0.386883735	0.307387214
0.176459416	-0.203680168	-0.500052935	0.293397506
0.172593145	-0.299055004	-0.433299917	0.301649356
0.173577811	-0.274764833	-0.450300651	0.299547765
0.17453825	-0.251072321	-0.466883083	0.297497884
0.172825277	-0.293328676	-0.437307784	0.301153913
0.171831081	-0.317853924	-0.42014252	0.303275842
0.173042448	-0.287971393	-0.441057356	0.300690399
0.170816876	-0.342872774	-0.402631782	0.305440477
0.173557149	-0.275274531	-0.449943913	0.299591864
0.174848414	-0.243421071	-0.472238206	0.296835897
0.175848862	-0.218741571	-0.489511432	0.294700622
0.172524975	-0.300736661	-0.432122923	0.301794853
0.172949176	-0.290272283	-0.439446959	0.300889473
0.168287248	-0.405274719	-0.35895655	0.310839506
0.170219272	-0.357614716	-0.392313871	0.306715953
0.17451489	-0.25164858	-0.466479757	0.297547743
0.172698029	-0.296467681	-0.435110789	0.3014255
0.174632795	-0.248740039	-0.468515451	0.297296095
0.176081905	-0.212992771	-0.493535027	0.294203234
0.173035978	-0.288131001	-0.440945646	0.300704209
0.172253211	-0.30744064	-0.427430796	0.302374882
0.170907269	-0.340642929	-0.404192455	0.305247551
0.169432597	-0.377020772	-0.378731538	0.308394969
0.170993525	-0.338515116	-0.405681715	0.305063452
0.17294601	-0.290350391	-0.439392292	0.300896231
0.172055429	-0.31231962	-0.424015989	0.302797013
0.172134177	-0.310377015	-0.425375622	0.302628938

0.174312987	-0.256629191	-0.462993819	0.297978666
0.174135959	-0.2609962	-0.459937342	0.2983565
0.169903512	-0.365404025	-0.386862119	0.307389886
0.167925913	-0.414188303	-0.352717917	0.311610711
0.172042435	-0.31264015	-0.423791649	0.302824745
0.171474631	-0.326646994	-0.413988234	0.30403662
0.173009346	-0.28878799	-0.440485819	0.300761051
0.174461766	-0.252959069	-0.465562544	0.297661126
0.173620536	-0.273710881	-0.451038314	0.299456577
0.171676258	-0.321673162	-0.417469429	0.303606283
0.171544115	-0.32493292	-0.415187918	0.303888318
0.170167783	-0.358884883	-0.391424879	0.306825848
0.170288061	-0.355917821	-0.393501531	0.306569137
0.171804666	-0.318505549	-0.419686447	0.30333222
0.172135022	-0.310356178	-0.425390205	0.302627135
0.173397562	-0.279211299	-0.447188562	0.299932474
0.171192693	-0.333601949	-0.409120449	0.304638364
0.171824053	-0.318027295	-0.420021177	0.303290842
0.174619547	-0.249066841	-0.468286722	0.29732437
0.171097967	-0.335938708	-0.407484947	0.304840541
0.167922504	-0.414272378	-0.352659073	0.311617985
0.172921479	-0.290955516	-0.438968764	0.300948586
0.172142313	-0.310176322	-0.425516087	0.302611574
0.169235875	-0.381873583	-0.375335047	0.308814835
0.173621429	-0.27368886	-0.451053727	0.299454672
-0.832694753	0.570500847	0.657998174	0.687064591
-0.833640488	0.547171056	0.674326737	0.685046093
-0.831703822	0.594945563	0.640889274	0.689179553
-0.831008636	0.612094715	0.628886552	0.690663301
-0.832831431	0.567129221	0.660357981	0.686772878
-0.833917753	0.540331369	0.679113846	0.684454322
-0.82861483	0.671146148	0.587556349	0.695772442
-0.830717366	0.619279882	0.623857641	0.691284963

-0.833356569	0.554174902	0.669424732	0.685652068
-0.833760732	0.544204827	0.676402805	0.684789455
-0.831713261	0.594712712	0.641052247	0.689159407
-0.832432028	0.576981876	0.65346209	0.687625331
-0.832153297	0.583857713	0.64864968	0.68822023
-0.829636515	0.645942795	0.605196221	0.693591843
-0.833465388	0.551490487	0.671303559	0.685419811
-0.831242601	0.606323161	0.632926073	0.690163945
-0.83285212	0.566618863	0.660715182	0.686728721
-0.829645576	0.64571926	0.605352673	0.693572503
-0.832843851	0.566822835	0.660572421	0.686746369
-0.826370118	0.726519672	0.548800322	0.70056337
-0.830882511	0.615206028	0.626708939	0.690932492
-0.831941215	0.589089454	0.644987975	0.688672881
-0.833431764	0.55231994	0.670723023	0.685491576
-0.832488576	0.575586909	0.65443843	0.687504639
-0.835694267	0.49650755	0.709786214	0.680662677
-0.833734716	0.544846594	0.675953632	0.684844981
-0.831342357	0.603862333	0.634648411	0.689951034
-0.835033593	0.512805351	0.698379354	0.682072766
-0.832998989	0.562995824	0.663250953	0.686415255
-0.834438761	0.527478911	0.688109304	0.683342325
-0.830150486	0.633263936	0.614070176	0.692494866
-0.832511286	0.575026701	0.654830521	0.687456169
-0.832922175	0.564890701	0.661924725	0.686579201
-0.831172367	0.608055727	0.631713447	0.690313847
-0.828889445	0.664371818	0.592297715	0.695186326
-0.834273298	0.531560629	0.685252502	0.683695476
-0.8328703	0.566170395	-0.338970935	0.57933721
-0.832744296	0.569278701	-0.341146444	0.58105648
-0.838221925	0.434154186	-0.246572555	0.506316222
-0.835320241	0.505734195	-0.296671531	0.545908655
-0.835029254	0.512912369	-0.301695548	0.549879057

-0.835882144	0.491872916	-0.286969997	0.538241686
-0.834958864	0.514648796	-0.302910876	0.550839512
-0.833384165	-0.446505864	0.669901201	0.64993041
-0.838450445	-0.57148304	0.757372949	0.722435478
-0.83643178	-0.521685732	0.722519725	0.693545746
-0.833584367	-0.451444517	0.673357773	0.652795552

Appendix K: Error Computation for Logsig – Logsig activation parameters

Va Error	Ps Error	Rr Error	MAE
0.147254569	0.011320588	0.047294593	0.06862325
0.147254668	0.011337098	0.047284401	0.068625389
0.147255254	0.011434878	0.04722404	0.068638057
0.147254569	0.011320599	0.047294586	0.068623251
0.14725463	0.011330726	0.047288334	0.068624563
0.14725457	0.011320761	0.047294486	0.068623272
0.147254569	0.011320608	0.04729458	0.068623252
0.147254569	0.011320647	0.047294556	0.068623257
0.147254569	0.011320591	0.047294591	0.06862325
0.147283885	0.01621218	0.04427494	0.069257002
0.14725457	0.011320746	0.047294495	0.06862327
0.147254948	0.011383918	0.047255498	0.068631455
0.147254569	0.011320597	0.047294587	0.068623251
0.147254571	0.011321022	0.047294325	0.068623306
0.147254569	0.011320588	0.047294593	0.06862325
0.147339248	0.025449985	0.038572305	0.070453846
0.147254569	0.011320592	0.04729459	0.06862325
0.147258102	0.011910186	0.046930625	0.068699638
0.14725457	0.011320722	0.04729451	0.068623267
0.147254574	0.011321385	0.0472941	0.068623353
0.147254569	0.011320592	0.04729459	0.06862325
0.147254569	0.011320591	0.047294591	0.06862325
0.147254569	0.011320611	0.047294579	0.068623253
0.147254569	0.011320592	0.04729459	0.06862325
0.147254586	0.011323477	0.047292809	0.068623624
0.147254569	0.011320626	0.047294569	0.068623255
0.147272804	0.014363251	0.045416311	0.069017455
0.147254569	0.011320599	0.047294586	0.068623251
0.147254569	0.011320587	0.047294593	0.06862325
0.147254569	0.011320597	0.047294587	0.068623251
0.147254569	0.011320634	0.047294564	0.068623256

0.147622336	0.072685214	0.009413295	0.076573615
0.147261875	0.01253974	0.046541992	0.068781202
0.147265604	0.013161864	0.046157946	0.068861804
0.147254571	0.011320912	0.047294393	0.068623292
0.147254569	0.01132061	0.047294579	0.068623253
0.147380865	0.032393989	0.034285668	0.071353507
0.147331667	0.024185016	0.039353189	0.070289958
0.14725458	0.011322471	0.04729343	0.068623494
0.147254572	0.011321139	0.047294253	0.068623321
0.14725458	0.01132248	0.047293424	0.068623495
0.147254824	0.011363179	0.047268301	0.068628768
0.147308078	0.020249021	0.041782938	0.069780012
0.147273192	0.014427991	0.045376347	0.069025843
0.147254569	0.011320624	0.04729457	0.068623254
0.14725457	0.011320746	0.047294495	0.06862327
0.147254569	0.011320588	0.047294593	0.06862325
0.147254571	0.011320894	0.047294404	0.068623289
0.147254569	0.011320589	0.047294592	0.06862325
0.147254569	0.011320596	0.047294587	0.068623251
0.147294524	0.01798741	0.043179064	0.069486999
0.147254582	0.01132279	0.047293233	0.068623535
0.147254569	0.011320592	0.04729459	0.06862325
0.147304676	0.019681384	0.042133349	0.06970647
0.147254801	0.011359389	0.04727064	0.068628277
0.147254569	0.011320594	0.047294589	0.068623251
0.147254569	0.01132059	0.047294592	0.06862325
0.14725458	0.01132241	0.047293468	0.068623486
0.147254571	0.011320916	0.04729439	0.068623292
0.147257187	0.011757482	0.047024891	0.068679854
0.147254569	0.011320666	0.047294545	0.06862326
0.147474399	0.048000805	0.024651348	0.073375517
0.147254713	0.011344588	0.047279777	0.068626359
0.147254572	0.011321162	0.047294238	0.068623324

0.147254569	0.011320589	0.047294592	0.06862325
0.147254569	0.011320591	0.047294591	0.06862325
0.147510182	0.053971469	0.020965568	0.074149073
0.147254569	0.011320623	0.047294571	0.068623254
0.147254644	0.011333062	0.047286892	0.068624866
0.147254569	0.011320589	0.047294592	0.06862325
0.147254569	0.011320591	0.047294591	0.06862325
0.147254569	0.011320646	0.047294557	0.068623257
0.147254569	0.01132063	0.047294566	0.068623255
0.147292445	0.017640593	0.04339316	0.069442066
0.147254569	0.011320595	0.047294589	0.068623251
0.147254569	0.011320597	0.047294587	0.068623251
0.147345943	0.026566972	0.037882773	0.070598562
0.1473054	0.019802107	0.042058824	0.06972211
0.14725457	0.011320862	0.047294423	0.068623285
0.147254569	0.011320593	0.04729459	0.06862325
0.147254569	0.011320597	0.047294587	0.068623251
0.147254569	0.011320643	0.047294559	0.068623257
0.147254569	0.011320598	0.047294586	0.068623251
0.147254569	0.011320589	0.047294592	0.06862325
0.147254569	0.011320591	0.047294591	0.06862325
0.147254569	0.011320609	0.047294579	0.068623253
0.147254569	0.011320588	0.047294593	0.06862325
0.147330708	0.024025018	0.039451959	0.070269228
0.147261316	0.012446471	0.046599569	0.068769118
0.147254569	0.011320591	0.047294591	0.06862325
0.15401093	0.138668304	0.351366046	0.21468176
0.154214244	0.172592841	0.330423923	0.219077003
0.154020612	0.14028387	0.350368733	0.214891072
0.15405032	0.145240914	0.347308676	0.215533303
0.153966028	0.131176092	0.3559911	0.213711073
0.154044696	0.14430248	0.347887985	0.21541172
0.152623149	-0.092892866	0.494312207	0.246609408

0.154214437	0.172624933	0.330404113	0.219081161
0.154214438	0.172625232	0.330403928	0.2190812
0.147308128	-0.979742588	1.041777758	0.722942825
0.153224343	0.007420606	0.432387206	0.197677385
0.154208162	0.171577984	0.33105041	0.218945519
0.153888242	0.118197015	0.364003278	0.212029512
0.154030966	0.142011505	0.349302238	0.215114903
0.154038422	0.143255611	0.348534233	0.215276089
0.153753616	0.095733748	0.377870187	0.209119184
0.152882072	-0.049689763	0.467642288	0.223404707
0.154212227	0.172256292	0.330631681	0.2190334
0.154175061	0.166054876	0.334459907	0.218229948
0.154041663	0.143796435	0.348200374	0.215346158
0.153258278	0.013082962	0.428891749	0.198410996
0.154047015	0.14468938	0.347649146	0.215461847
0.153977739	0.133130273	0.354784755	0.213964256
0.153353592	0.028986838	0.41907405	0.200471493
0.153849107	0.111666962	0.368034377	0.211183482
0.153998377	0.136573737	0.352659054	0.214410389
0.154214482	0.172632464	0.330399464	0.219082136
0.154214458	0.172628572	0.330401866	0.219081632
0.154051993	0.145520019	0.34713638	0.215569464
0.153982412	0.133909884	0.354303489	0.214065262
0.154064135	0.147546021	0.345885699	0.215831952
0.152802902	-0.062899898	0.475797101	0.230499967
0.154043273	0.144065122	0.34803451	0.215380968
0.153898243	0.119865774	0.362973128	0.212245715
0.15379112	0.101991543	0.374007157	0.20992994
0.154051721	0.145474611	0.347164411	0.215563581
0.154200447	0.170290599	0.331845132	0.218778726
0.153966068	0.13118278	0.355986971	0.21371194
0.153999435	0.136750428	0.352549979	0.214433281
0.153253942	0.012359439	0.429338391	0.198317257

0.154209379	0.171780962	0.330925109	0.218971816
0.153433082	0.042250208	0.410886373	0.202189888
0.15404111	0.143704201	0.348257312	0.215334208
0.147478479	-0.951318283	1.024231011	0.707675925
0.153924929	0.12431855	0.360224363	0.212822614
0.153829187	0.108343324	0.370086108	0.210752873
0.154039628	0.14345684	0.348410011	0.21530216
0.153883788	0.11745379	0.364462082	0.21193322
0.154204012	0.170885519	0.331477879	0.218855803
0.152917739	-0.043738374	0.463968407	0.220208174
0.153920072	0.123508104	0.360724663	0.212717613
0.153919044	0.123336591	0.360830541	0.212695392
0.153949371	0.128396837	0.357706775	0.213350995
0.154013188	0.139045201	0.351133382	0.21473059
0.154204692	0.170998953	0.331407855	0.2188705
0.153013297	-0.027793872	-0.545874372	0.24222718
0.152166745	-0.169047221	-0.458676575	0.259963513
0.15155556	-0.271027837	-0.39572242	0.272768606
0.151684818	-0.249460295	-0.409036385	0.270060499
0.15250951	-0.111854497	-0.493982496	0.252782167
0.15105642	-0.35431303	-0.344309229	0.283226226
0.15123191	-0.325031269	-0.362385297	0.279549492
0.150624166	-0.426437672	-0.299785613	0.292282484
0.153214815	0.005830743	-0.566631348	0.241892302
0.15109691	-0.347556907	-0.348479885	0.282377901
0.151630883	-0.258459733	-0.403480898	0.271190505
0.151441469	-0.290064795	-0.383970623	0.275158962
0.151369531	-0.302068132	-0.376560783	0.276666149
0.152702274	-0.079690396	-0.513837874	0.248743515
0.150890534	-0.381992219	-0.327222454	0.286701736
0.151246689	-0.322565321	-0.363907564	0.279239858
0.151742902	-0.23976856	-0.415019238	0.268843566
0.15114102	-0.340196834	-0.353023367	0.281453741

0.151150826	-0.338560689	-0.354033385	0.2812483
0.151416437	-0.294241633	-0.381392198	0.275683423
0.150860549	-0.38699556	-0.324133817	0.287329975
0.15214666	-0.172398504	-0.456607778	0.260384314
0.152813272	-0.061169601	-0.525271037	0.24641797
0.151118793	-0.343905638	-0.350733867	0.281919433
0.151096922	-0.347555003	-0.34848106	0.282377662
0.151171235	-0.335155348	-0.356135552	0.280820712
0.151005957	-0.362733078	-0.339111408	0.284283481
0.151346279	-0.305947952	-0.374165713	0.277153315
0.151290927	-0.315183855	-0.368464252	0.278313011
0.15198246	-0.199796535	-0.439694565	0.26382452
0.152373225	-0.134594546	-0.479944724	0.255637498
0.151644879	-0.256124396	-0.404922537	0.27089727
0.151393919	-0.297998935	-0.37907276	0.276155204
0.150982057	-0.366721	-0.336649604	0.284784221
0.151745596	-0.239319	-0.415296758	0.268787118
0.150642987	-0.423297282	-0.301724223	0.291888164
0.151981952	-0.199881239	-0.439642276	0.263835156
0.151987274	-0.198993214	-0.440190467	0.263723652
0.151430053	-0.291969686	-0.382794705	0.275398148
0.151064543	-0.35295758	-0.345145969	0.283056031
0.151636892	-0.25745708	-0.404099851	0.271064608
0.152594376	-0.097693898	-0.502724044	0.251004106
0.152040312	-0.1901435	-0.445653527	0.262612446
0.150742609	-0.406674562	-0.311985675	0.289800949
0.150904706	-0.379627646	-0.32868214	0.28640483
0.15143452	-0.29122429	-0.383254849	0.275304553
0.151145307	-0.33948152	-0.353464941	0.281363923
0.150825197	-0.392894278	-0.32049245	0.288070642
0.151890116	-0.215204857	-0.430182778	0.26575925
0.150970588	-0.368634748	-0.335468219	0.285024518
0.152978743	-0.033559422	-0.542315212	0.242951126

0.152135055	-0.174335015	-0.45541234	0.26062747
0.150918535	-0.377320155	-0.330106588	0.286115093
0.15152851	-0.275541339	-0.392936168	0.273335339
0.15141578	-0.294351199	-0.381324562	0.27569718
0.152032964	-0.191369647	-0.444896608	0.262766406
0.15092331	-0.376523336	-0.330598476	0.286015041
0.152275971	-0.150822128	-0.469927196	0.257675098
0.150868528	-0.385664088	-0.324955754	0.28716279
0.151820031	-0.226898911	-0.422963864	0.267227602
0.152119836	-0.176874371	-0.453844758	0.260946322
0.151205402	-0.329454219	-0.359654944	0.280104855
0.15197834	-0.200483911	-0.439270237	0.26391083
0.151644558	-0.256177908	-0.404889503	0.27090399
0.151521705	-0.276676914	-0.392235161	0.273477926
0.15225371	-0.154536573	-0.467634214	0.258141499
0.153041519	-0.023084923	-0.548781276	0.241635906
0.15220691	-0.162345415	-0.462813699	0.259122008
0.151093257	-0.34816648	-0.348103586	0.282454441
0.151482875	-0.283155973	-0.388235541	0.274291463
0.151509871	-0.278651492	-0.391016224	0.273725862
0.151082948	-0.349886684	-0.347041678	0.282670437
0.151968912	-0.202057086	-0.438299093	0.264108364
0.151594432	-0.264541755	-0.399726375	0.271954188
0.151929121	-0.208696527	-0.434200467	0.264942038
0.15265926	-0.086867611	-0.509407273	0.249644714
0.151980473	-0.200128063	-0.439489907	0.263866148
0.152361413	-0.136565405	-0.478728084	0.255884967
0.152343799	-0.139504579	-0.476913687	0.256254022
0.150806684	-0.395983255	-0.318585578	0.288458506
0.151083987	-0.349713185	-0.347148782	0.282648652
0.151450841	-0.288501036	-0.384935954	0.27496261
0.151797051	-0.230733302	-0.420596837	0.267709064
0.151761008	-0.236747324	-0.416884292	0.268464208

0.1510283	-0.359005093	-0.341412749	0.283815381
0.151846171	-0.222537367	-0.42565631	0.266679949
0.150900752	-0.380287291	-0.328274931	0.286487658
0.150842527	-0.390002639	-0.322277502	0.287707556
0.151121388	-0.343472582	-0.351001199	0.281865057
0.151341767	-0.306700771	-0.373700987	0.277247841
0.151171134	-0.335172177	-0.356125163	0.280822825
0.151830479	-0.22515574	-0.424039949	0.267008723
0.151445649	-0.289367282	-0.384401208	0.27507138
0.150978142	-0.367374283	-0.336246323	0.284866249
0.151546571	-0.272527701	-0.394796532	0.272956935
0.151326106	-0.30931395	-0.372087832	0.277575963
0.150972126	-0.368378093	-0.335626656	0.284992292
0.151095872	-0.347730208	-0.348372904	0.282399661
0.151498767	-0.280504285	-0.389872468	0.273958506
0.151867239	-0.219021941	-0.427826435	0.266238538
0.152267364	-0.152258154	-0.469040715	0.257855411
0.150902731	-0.379957181	-0.328478713	0.286446208
0.152348413	-0.138734672	-0.477388963	0.256157349
0.151129462	-0.342125447	-0.351832806	0.281695905
0.151856413	-0.220828325	-0.426711327	0.266465355
0.151861648	-0.21995487	-0.427250524	0.266355681
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-0.849390087	0.571184125	0.701682487	0.7074189
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-0.849793168	0.503927142	-0.256798775	0.536839695

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-0.849855856	-0.50653281	0.74965831	0.702015659
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