Development of an Objective Tool for Aphasia Assessment through Artificial Neural Network

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CHAPTER I

INTRODUCTION

A correct diagnosis is three-fourths the remedy.

-Mahatma Gandhi

Aphasia is manifested as language impairment associated with difficulty in production or comprehension of speech. Post stroke rehabilitation plays a vital role in recovery of these individuals and has been repeatedly suggested that immediate intervention must be initiated at the earliest after the occurrence of stroke.

According to National Aphasia Association (2009), a person is considered to be aphasic, when s/he has a language impairment associated with difficulty in production or comprehension of speech with or without impaired reading and writing abilities. Aphasia is generally caused due to an injury to the brain. A common cause of aphasia includes stroke, road traffic accidents, head injuries, brain tumors, infections etc (Jenkins &Birkett-Swan, 2010).

Prevalence rate of stroke in individuals aged above 65 ranges from 46-73 per 1000 persons. Aphasia can be noted in at least 30% of the stroke survivors (Pendlebury&Rothwell, 2009). The effects of aphasia are not only manifested as speech and language impairment but as overall difficulty in daily communicational skills, increase in cost of patient care post stroke and therefore a poor quality of life. The impact of aphasia on caregivers has been widely documented across literature (Evans et al., 1992). Post stroke rehabilitation plays a vital role in recovery of these individuals and has been repeatedly suggested that immediate intervention should be initiated as early as possible after the occurrence of stroke. The symptoms in aphasia can manifest in a heterogeneous manner, thus the classification of aphasia into sub variants would be essential.

Classification of aphasia and its symptoms has been given great importance right from its early inception by Broca on his patient Mr. Tan (1861) as "a loss of the ability to co-ordinate the movements associated with articulated speech". Similar grouping of aphasia based on symptoms exhibited by PWA (persons with aphasia) can be seen across the literature (Wernicke, 1874; Lichtheim, 1885; Marie, 1906; Dejerine, 1914; Luria, 1964; Jakobson,1956; Geschwind, 1965; Alajouanine, 1968; Goodglass et al., 1976; Ardila, 2010). Recent classification system of Boston classification system (Goodglass, Kaplan & Barresi, 2001) is one among the currently accepted classification systems. According to Goodglass & Barresi, (2000) aphasia can be classified based on characteristics of verbal expression (non-fluent or fluent).

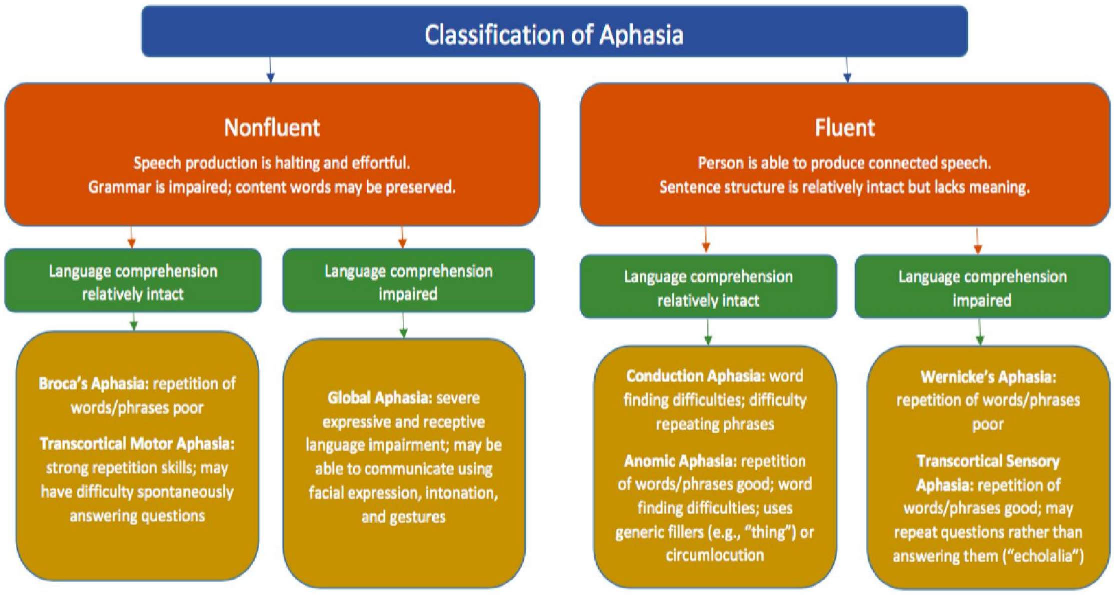

Figure 1: Pictorial representation of current aphasia classification system Goodglass & Barresi (2000)

The assessment in the clinical scenario for persons with aphasia (PWAs) involvesstandardized aphasia test materials, or shortlisted subtests of standardized diagnostic aphasia tests which are administered by diagnostic speech and language pathologists

(SLPs).The formal tests have n important role in the diagnostic formulation of individuals and thereby gives information pertaining type/variant of aphasia and its severity. The formal assessment aims to identify and summarise the linguistic abilities and shortcomings of the PWA and is often organised and executed in a periodic manner to observe variations that occur over time. The results and observations from the formal assessmentact as a foundation for therapy and help in planning treatment goals and individualizing intervention (Goodglass, Kaplan, Weintraub& Ackerman, 1976).

Establishment of an individual's current communicative, linguistic, and cognitive level is most often the other prime purpose of a formal aphasia assessment. The motive of an assessment which is formal in its natureallows the determination of the presence, character, and severity of the disorder, as well as to map the strengths and weaknesses of language (Murray &Coppens, 2012). However, there exists a well known consensus among researchers that the formal aphasia assessment by itself is not a stand alone valid option when it comes to accurately understanding an individual's communicative proficiency (Davis & Wilcox, 1985; Damico, Simmons-Mackie & Wilson, 2006; Lesser & Milroy, 1993).

Currently to evaluate aphasia we use various standardised screening tests such as Aphasia Language Performance Scale (ALPS)-Keenan &Brassell, (1975); Frenchay Aphasia Screening Test (FAST)- Enderby, (1987);The Mississippi Aphasia Screening Test (MAST)-Nakase-Thompson, (2004) anddiagnostics tests such as Minnesota Test for Differential Diagnosis of Aphasia (MTDDA)-Schuell, (1973);The Boston Diagnostic Aphasia Examination (BDAE)- Goodglass, & Barresi, (2000); Western Aphasia Battery (WAB)-Shewan&Kertesz (1980). In Indian scenario various adaptations of standardised test have been carried out, such as WAB in languages such as Kannada by Shyamala and Vijayashree in 2007; Telugu by Pallavi and Shyamala in 2010; Bedside Screening Test for Aphasics in

Kannada by Ramya and Goswami in 2011 and in Malayalam by Kanthima and Goswami in 2011.

Aphasic behaviours (verbal or non-verbal) exhibited by PWA can be distinctively different on one hand or overlapping on the other to the extent of leading to misdiagnosis. The major cause of this is 'variability' which is the hallmark of aphasic syndromes. Therefore individual differences must be accounted for to prevent such errors. Performance of every PWA is different from another. This poses a great difficulty in reaching an appropriate diagnosis using the available subjective assessment tools. For instance, cases wherein the presentation of symptoms and designation of WAB doesn't match; example being, when seen based on experiences it will be conduction aphasia but WAB indicates anomic aphasia. Current standardised tests are highly subjective and little to no objectivity involved in them. With advent of technology in the field of communication disorders more and more tests are going digital to assist better service delivery for professionals. Once the evaluation is made there is no quantification of extent to which a condition might be possible using the present. Therefore there is a need for an objective tool that can assist professionals in classification of aphasic symptoms and provide an estimate on prognosis of an individual.

Although rehabilitation of individuals with aphasia has become more common, selecting domains and controlling parameter that needs to be worked upon for rehabilitation is still challenging for novice therapists. Therefore, it is necessary to develop a tool which not only helps in the diagnosis but also point towards an empirical approach, for predicting the possible domains to be worked upon during his/her rehabilitation.

Application of Artificial Neural Networks (ANNs) has been widely studied over the last decades in various fields such as atmospheric sciences (Gardner & Dorling, 1998), energy system (Kalogirou, 2000; Kalogirou, 1999), medicine (Baxt, 1995; Wu et al.,1993;

Agatonovic-Kustrin& Beresford, 2000) and ecological modelling (Lek& Guégan,1999). Using weights manipulation a sensitivity analysis can evaluate the relations between the input and output variables in ANN (Garson, 1991). Therefore, we expected that aphasic symptoms can be explored by a successfully trained ANN model.

1.1 Need for the study

Rehabilitation begins with assessment and diagnosis. An accurate diagnosis points to the correct treatment for which one requires a proper assessment tool. Hence it is important to have standardized language tests to assess aphasia and its types. The standardised tests as stated in the above mentioned paragraphs is subjected to bias and variability and has to be cross verified with objective measures such as ANN

1.2 Aim

To build an objective tool that provides assistive objective evaluation along with confidence index on aphasic individuals and possible rehabilitation domains.

1.3Objectives

The objectives of the present study were

(i) To build an objective tool to derive scores to classify and quantify aphasic symptoms.

(ii) To check the accuracy of the developed tool through preliminary analysis.

CHAPTER II

REVIEW OF LITERATURE

ANNs are being incorporated in many medically related applications and scientific study.They provide an effective means to help diagnosticians analyse, model and make sense of complex clinical data across a broad range of medical applications.

The medical utilizations have been finding its use in the field of communication sciences since the 2000s in India. A study (Geetha, 2000), involving ANNs used for disfluency classification in children has been attempted as an attempt to incorporate artificial intelligence into communication sciences. The exploration of neural networks has been limited in other domains however especially in the area of language disorders.

2.1 Aphasia- Assessment and Classification

Aphasia is the most common consequence of a brain damage in the language arena of disability. Use of wrong words and empty phrases, impairments with reading and writing or articulation (inclusive of supra-segmental features) are a few examples of characteristics displayed by an individual suffering for aphasia. The brain structures responsible for various language function are effected as a result of the brain damage. This damage may bea stroke, a traumatic head injury, or a tumour in the cerebrum. There are several types of aphasia, and only a skilled diagnostician can classify what type of aphasia it is.

Representation of language has been developed by the proposal of several neuro-anatomical models for more than 100 years, with the one proposed by Wernicke in 1874 being very well known. The current understanding reveals that the brain consists of vast neuronal networks, out of which some are considered to be responsible for language functions. The brain specific location of aphasic syndromes is rather indistinct as per current review as more than one aphasic symptoms can be variably affected by damage to more than one structure.

The assessment of language skills in patients with aphasia has been considered as one of the developed components in the process of neuropsychological assessment. The reason attributing to this strong comment is the possible exploration of the same in the early 1990s. Even though, the assessment has been reported to have been explored early in time however the interest in language has been found to be limited on closer inspection. The focus has always been non language domain. Additionally, scrutiny of the diagnostic procedures and protocols adopted revealed several loop holes. This may be due to the evolving nature of language assessment overtime.

Classification regarding type of aphasia is an issue that has received mixed reviews. Brookshire (1983) reports of high variability in aphasia labelling process attributing this variability to the beliefs, opinions and the biases of the diagnosticians. An additional variation is also brought about with the decision of whether the labelling must be mandatory and if yes, then the classification system used for the same. Complexity and severity of a given patient's language impairment have been commented to not be explicitly described using classification system process. In contrast, supporters of classification have been considering the system to be an efficient method for describing symptoms that can be used to enhance communication among professionals and also plan the treatment accordingly. The various classification systems imply the orientation of their founders; clinical, psycholinguistic, anatomical or physiological. Due to this constant debate over the pros and cons of classification and the use of labels often make diagnosticians and clinical researchers uncomfortable in classifying the language deficits of aphasic patients. In order to combat this difficulty, many have adopted formal test instruments to label aphasia. One example is the Western Aphasia Battery-WAB (Kertesz, 1982).

The need for use of language tests vary with the apparent expression of deficits. In some situations, the deficits in language can be very straight forward which translates to reduced requirement of detailed testing to determine normalcy. In such situations, the language tests can aid to better define the problem. This allows the diagnostician in the counselling process and subsequently to describe the language impairment to the family, care giver for the patient, and other members in he multidisciplinary group.. Additionally, the description allows speech language pathologists to plan an effective treatment option. Classification of aphasia types or syndromes, determination of overall severity of aphasia, and an information-processing approach are the well known methods to allow description for the language impairment. The approach of aphasia types or syndromes would be discussed in detailed in the review.

Swindell, Holland, and Fromm (1984) reported unequal agreement in the clinical diagnosis of aphasia types. The classification utilized comparison of interpreted aphasia variants using two major diagnostic tools: the Boston Diagnostic Aphasia Examination and the Western Aphasia Battery (Wertz, Deal, & Robinson, 1984). A considerable number of patients were found to be unclassifiable according to methods prescribed by the Boston Diagnostic Aphasia Examination (Benton, 1994). Eventhough there has not been an identified gold standard method for classifying variants of aphasia, the use of aphasia type labels remains the most common clinical method for defining language impairment.

2.1.1 Aphasia Standardised Test Materials

BDAE and WAB are the two standardised diagnostic tests incorporated dueing aphasia examination by slps which would be compared in the following;

2.1.1.1 Boston Diagnostic Aphasia Examination (BDAE;Goodglass& Kaplan, 1983)

BDAE allows determination of normalcy of language along with classification of aphasia variant (e.g., Broca's aphasia). Revised edition has been developed in 1983.The addition include score conversion to percentile data and normative. BADE is frequently reported in the literature; thereby allowing the comparison of patient data to that of new patients.

2.1.1.2 Western Aphasia Battery (WAB:Kertesz, 1982)

The WAB is a comprehensive test to assess language that aids the diagnosticians to effectively categorises patients with language impairment according to aphasia syndromes and its variation from neurological normal language skills. An overall score of severity of language impairment (AQ or Aphasia Quotient) allows comparison objectively.Skills associated with language such as reading, writing and cognition are also accountable using WAB.

Both WAB and BDAE allow aphasia variant classification. But they differ in terms of ease of administration and interpretation.They however differ in various aspects. The directions are clearer in WAB and even the scoring pattern is easier to interpret in comparison with BDAEThe stimuli used in WAB have been reported to be more familiar to the people when compared to the stimuli used in BDAE (picnic scene picture in WAB versus to the cookie theft picture in BDAE.) BDAE has been reported to containcomparatively challenging items to test auditory comprehension than the WAB. Both the WAB and the BDAE incorporate ratings of fluency based on spontaneous speech samples.

Table 1.

Cut off scores to determine the type of Aphasia (WAB, Kertez 1982)

	Fluency	**Comprehension**	**Repetition**	**Naming**
Global	0-4	0-3.9	0-4.9	0-6
Broca's	0-4	4-10	0-7.9	0-8
Isolation	0-4	0-3.9	5-10	0-6
Transcortical Motor	0-4	4-10	8-10	0-8
Wernicke's	5-10	0-6.9	0-7.9	0-9
Transcortical Sensory	5-10	0-6.9	8-10	0-9
Conduction	5-10	7-10	0-6.9	0-9
Anomic	5-10	7-10	7-10	0-9

The need to determine the aphasia variant finds its application in medical settings where multidisciplinary communication is inevitable in order to reach effect treatment.Additionally, a clear description of a given patient allows the inclusion in research specific to the variant subtypes of aphasia.Further in depth research is required to understand the classification of aphasia.

The review highlights the need for objectivity to avoid the apprehensions of diagnosticians during the aphasia variant classification. This can be made possible with incorporation of neural networks using the most commonly used diagnostic test of WAB.

2.2 Artificial Neural Network

The field of science and technology in the recent times have widely been exploring the utilization of Artificial neural networks (ANNs). The possible variations in a data along with considerable large amount of input data is utilised using advanced computational methods, which are analysed on the basis of the results from previous trainingdata. The output is determined based on the sample database as in the probability of a certain pathology or classification of biomedical objects. ANNs have found their applications in analysis of blood and urine samples of diabetic patients, diagnosis of tuberculosis, leukemia classification

,analysis of complicated effusion samples, and image analysis of radiographs or living tissue research due to the flexibility of type of input data that is provided in an ANN.
ANNs are also termed as neuro-computers, connectionist networks, parallel distributed processors, etc.

ANN is an enormous parallel distributed processor that possesses a natural ability to sort experimental knowledge and make it usable by the recipient. It resembles the functioning of the human brain in two aspects: (1) Knowledge is obtained via the process of learning, (2) Storage of knowledge is done using the interneuron connection strength, known as weights. In order to under stand ANN, it can be described as a unit of "biologically" inspired networks possessing the ability to initiate the brain's activity to make decisions and draw conclusions when provided with new, complex and disturbance involving information (Haykins, 1994).

2.2.1 Characteristics of Neural Networks

ANN obtains its computing power with the help of its enormous parallel distributed structure and the ability to generalise post the learning process. This important step of generalisation involves the production of accurate outputs doe the input data which was not acquainted with during the training phase. The ability of ANNs to solve complex and large scale problems can be attributed to the above mentioned information processing capacities. A complex problem of interest is decomposed into a number of relatively simple tasks and NNs are assigned subsets of tasks (eg; pattern recognition, associative memory, control) that match their inherent capabilities (Haykin, 1995).

Zurada(1992) describes the useful properties of ANNs:

1. Non-linearity: Since the ANN is made of neurons which are by themselves non linear and therefore the neural network is considered non linear bunch of neurons. Non linearity allows easy analysis when the input is non linear in nature (such as speech signal).
2. Input-Output mapping: Supervised learning mechanism involves modifying the synaptic weights by the virtue of training samples.The samples are made in such a way that each would contain a unique input signal and the corresponding desired response. The developed network is provided with a random sample from the set of samples and the parameters are modulated to reduce the gap between the actual response and the desired response.The training in this manner continues till the network reaches a steady state. Steady state here means a condition where no significant changes in weight leads to difference in results. The training samples can be fed again to the network however in a different order. Thus, the network learns from the examples by constructing an input-output mapping for the problem at hand like the supervised leaning paradigm.
3. Adaptivity: ANNs are equipped in themselves to adapt the synaptic weight to the various changed in the environment. For instance, anANN trained to operate in a specific environment can be easily retrained to analyse data in a different environment with minor changes.
4. Response evidence: The neural network requires the output in terms of classified data as well as the certainty with which the decision was made. Therefore the information can be used to avoid ambiguous data which improves the efficiency of classification.
5. Information from context: Structure and activation state of the ANN represents the knowledge. The overall activity of the neurons affects every constituting neuron and therefore the data is dealt with by the ANN in a natural manner.
6. VLSI implementation: The parallel nature of a neural network allows quick computation.This allows analysis of very large data using very-large scale integrated

(VLSI) technology. This allows a capture of truly complex behaviour in a highly hierarchical way, and there by allows the use of anANN as a tool for real time applications involving pattern recognition signal processing and control.

7. Uniformity of analysis and design: Same notation is made use of irrespective of the domain and application related to ANNs.
8. Neurobiological analogy: The design of a NN adapts the decision making ability of the human brain however only faster and with more power.

2.2.2 Structure and function of ANN

The typical architecture of an ANN consists of three layer system consisting of:

1. Data entering the network via Input Layer

2. Hidden Layers between the input and the output layers.

3. Response of network is provided by the Output Layer

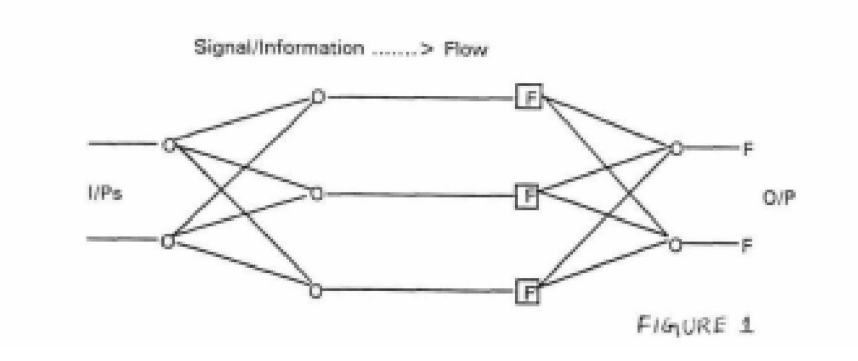

Figure 2: Architecture of an Artificial Neural Network

2.2.3 Working of ANN

McCullock and Pitta (1943), regarded as pioneers in the field of NNs outlined the first model of an elementary neuron n 1943 (Roal and Mankame, 1996).

The structure of an ANN is a set of processing units (nodes) arranged in rows. Inputs nodes are interconnected by simple connections with an internal layer of hidden nodes and a single output mode. Rather than having a fixed algorithmic approach to classification problems, an ANN is sequentially presented with a set of supervised training cases input data passes with correct output. The ANN modifies its behaviour in this process of training by adjusting the strengths or weights of the connections until its own output conveys to the known correct output. The information 'learned" by the ANN is stored in the weight of the network giving to the connections between nodes. Thus ANNs are designed to realise very specific computational tasks/ problems by the highly inter-connected, parallel computational structures with many and relatively simple elements.

2.2.3.1 Multi-Layer Perceptron

Multi-Layer Perceptron are an example of 'feed forward' nets with one or more layers of nodes between the input and output nodes which are not directly connected to both input or output nodes. They have been found to be more effective in comparison to single layer perceptions.

The capabilities of MLPS can be attributed to the non-linearity used within the nodes. Three layers are known to be efficient for predominantly complex decisions regions. (Lippman, 1987).The number of nodes in the first layer traditionally are regarded as sufficient to provide three or more edges for each convex area generated by every second layer node. There should thus be more than three times as many nodes in the second as in the first layer.

2.2.4 Uses of ANNs

Some of the uses of ANNs (Raol&Mankame, 1996) include:

- Information storage/recall

- Pattern recognition/classification

- Non-linear mapping between high dimensional spaces

- Time-series prediction as in cases of forecasting weather, detection of faults/failures in systems like power plants and aircraft sensors.

The application of ANNs in medical diagnosis has undergone severe scrutiny. The general application of ANNs in medical diagnosis have been applied in the diagnosisof cancer, metabolic diseases, reproductive organ related diseases etc. The large amount of input data which act as variables in the diagnostic process of such diseases requires the development of tools to enhance the quality and accuracy of diagnosis.

Hence from the above review of literature it is evident that scores obtained in different subsections of WAB namely Fluency, Auditory Verbal Comprehension, Repetition and Naming could be helpful altogther or individually in the differential diagnosis of various types of Aphasia. Also it can be seen from the review of Artificial Neural Networks (ANNs) that these software systems are very useful in building up models and they are mainly helpful in modelling complex, noisy and varying data.

It is well known that language abilities of persons with aphasia show a wide variety of variation which also determines the course of treatment. Hence the present study aims to create a model to differentially diagnose the neurological adult language disorder of Aphasia using an Artificial Neural Network.

The neural network used in the present study is Multi Layer Perception (MLP). Initially the study aims at training the neural network system, by using scores of performance of PWA on different language domains in WAB as the input and the diagnostic labels of different types of Aphasia as the output. Once the network is trained and a model is created, the efficiency of the model is to be checked, where the input consisting of scores of performance of PWA on different language domains in WAB are given and the network model has to predict the output or to which diagnostic category does the language disorder belong. This would also be co-related with the diagnosis of experienced speech language pathologists for the purpose of verification.

The model that has been developed as part of the currentproject in discussion is a neural network model with four inputs which are a combination of scores of language domain (Fluency, Auditory verbal comprehension, repetition, naming) of patients as per the Western Aphasia Battery and the type of aphasia variant resulted based on these scores. The presence of the aphasia variant is 1 and absence of any other variant is 0. In this model two hidden layers have been used. Output layer consists of one node which represents the type of aphasia. The input layer of a neural network is determined fromthe characteristics of the application input.. In this model we chose one hidden layer with 80 neurons and logistic sigmoid functions.

Chapter III

Method

This study was conducted at the All India Institute of Speech & Hearing, Mysuru after obtaining an ethical clearance from the Institutional review board for conducting research involving human subjects (AEC, 2009). The study was undertaken and exercised in two phases i.e. Phase I included the development of the tool using MATLAB (The MathworksInc, R2015b) software. In Phase II of the study testing of the developed tool was carried out.

3.1 Phase I – Building and training the ANN

ANN. MATLAB version 8.5.0.197613 (The Mathworks Inc, R2015a) software was used for building the ANN . Feed forward neural network was built. Optimal number error approach was used to specify the maximum number of training epochs, learning rates, number of nodes in a hidden layer. During training phase of the ANN, parameters such as number of nodes were varied between 6 and 24 with various learning rates in increments of 0.05 from 0.01 to 1.0. Based on the variable of mean square error (MSE) among the measured data and the model output the ANN was configured.

To avoid over generalization of the trained neural network the data was divided into two set, first was for model training (80%) by computing the gradient and revise the network and the second was for model testing (20%) for model testing using error validation. Randomization of the model weights will be done during the training process and was terminated when over fitting of the data was seen for validation set.

Four hundred individuals diagnosed with aphasia were recruited as participants. The data of the participants were picked retrospectively. A language deficit as part of one of the domains of the WAB subsections was the only inclusion criteria; post stroke duration and the degree of severity of the condition were not considered. Cases with sub cortical lesion and crossed aphasia were not considered as the study is in its preliminary phase and heterogeneity to a greater extent may have affected the confidence levels of ANN. Consent was obtained from the institute where data was collected. Patients with neuro-generative diseases and/or comorbid conditions affecting memory like Alzheimer's disease , primary progressive aphasia were excluded from the study.

3.1.1. Data

The participants were one hundred thirty six women and two hundred sixty four men with aphasia (Table 2). The participants were selected on retrospective basis The PWAs were aged

18- 70 years having being diagnosed as person with aphasia post stroke (ischemic/hemorrhagic). The time since the onset of aphasia was not controlled as a variable.

Table 2

Summary of participants of Phase I

	Diagnosis	Males	Females	Total
1.	Global Aphasia	41	15	56
2.	Broca's Aphasia	75	19	94
3.	Transcortical Motor	10	8	18
4.	Anomic Aphasia	27	15	42
5.	Isolation Aphasia	6	4	10
6.	Wernicke's Aphasia	32	20	52
7.	Transcortical Sensory	14	6	20
8.	Conduction Aphasia	30	21	51
9.	Non- Aphasic	29	28	57
	Total	**264**	**136**	**400**

3.1.2 Procedure

The data on WAB was subjected to two different types of compatibility check.

3.1.2.1 Compatibility check -1

In the first variant, the scoring on the domains on WAB, details of linguistic profiling like presence of paraphasia, circumlocution etc from 250 case files was provided and the diagnosis was made on the case files was given to 3 judges. The three judges were required to have experience of more than 10 years in diagnosing and treating cases with aphasia. The task of the judges was to correlate the findings provided by them with the diagnostic label and decide if the label was highly agreeable, agreeable or less agreeable (on a three choice goodness rating). It was ensured that case files with different diagnostic labels were subjected to rating.

Table 3

Format of Familiarity check-1

Identification Label	Aphasia Type	Goodness Rating		
		Highly agreeable	Agreeable	Less Agreeable
X	XX	✓	-	-

Instructions:Indicate using (✓) tick mark

Table 3: Format of Familiarity check-1

3.1.2.2 Diagnostic labels

In the second type of familiarity check, the details on WAB, details on linguistic profiling of another 250 case files (extracted retrospectively as in the previous section) was given to three other judges (other than the one's participated in the previous type of familiarity check). The experience for the recruitment of judges remained the same as in the previous type. Here the task of the judges was to label the aphasia variant as per the standard classification. The scores or the cut-off was given to the judges for minimizing the load on them. The judges were expected to write the label which they felt apt.

Table 4

Format of Familiarity check-2

Case Number	Aphasia Type							
	Global	Broca's	TMA	Anomia	Conduction	Wernicke's	TSA	Non Aphasic
X	-	-	-	-	✓	-	-	-

Instructions:Indicate using (✓) tick mark

The diagnostic label specified was taken into consideration while consolidating the final set of case details used to train the ANN. The diagnostic labels which are uniform across the judges were considered. Thus after the familiarity check, the 400 cases were shortlisted to train ANN.

3.1.2.3 Training of ANN

Aphasic profiles of all the shortlisted 400 participants were loaded onto MATLAB version 8.5.0.197613 (The MathworksInc, R2015a) software. A feed forward neural network was built using the ANN. Maximum number of training epochs, learning rates, number of nodes in a hidden layer were determined on the principle of optimal number error approach.

The training phase involved variation of nodes from 6 to 80 at various learning rates with increase by 0.05 from 0.01 till 1.0.Based on mean square error (MSE) among the measured data and the model output , modelling of the ANN was achieved.

To avoid over generalization of the trained neural network the data was divided into two set, first was for model training (70%) by computing the gradient and revise the network and the second was for model testing (30%) for model testing using error validation.

3.2 Phase II: Evaluating the efficacy of the ANN

The efficacy of ANN was determined by considering new cases. The diagnosis of the new cases was confirmed by three experienced speech-language pathologists with 3-7 years of experience.

3.2.1 Participants

Ten Individuals who reported to a reputed speech and hearing Institute with a suspected complaint of aphasia.

3.2.2 Procedure

3.2.2.1 Evaluation by SLPs

The participants were evaluated by three SLPs (the Co-investigator, the Research officer and one other SLP). Details of the SLP's are summarised in Table 5. All the SLP's were experienced in working with assessment and management of aphasia.

Table 5

Summary experience of SLPs in Phase II

Details of SLP's	**Years of experience**
SLP 1	15+
SLP 2	6
SLP 3	3

Table 6

Format for Diagnosis by SLPs

Case Number	**Aphasia Type**							
	Global	**Broca's**	**TMA**	**Anomia**	**Conduction**	**Wernicke's**	**TSA**	**Non Aphasic**
XX	-	-	-	-	✓	-	-	-

3.2.2.2. Evaluation by Developed Tool

Using the developed ANN, the evaluation was repeated. In order to ensure that the findings are appropriate, the details of new cases were subjected to a CROSS CHECK.

The crosscheck was carried by involving two experienced speech-language pathologists. The speech language pathologists were asked to diagnose the 10 cases in phase I, on the basis of WAB scores as well as details on linguistic profiling.

Table 7

Format for Crosscheck Diagnosis by SLPs

Case Number	**Diagnosis Method**	**SLP 1**	**SLP 2**	**SLP 3**	**ANN**
	WAB Scores	Conduction	Conduction	Conduction	Conduction
	Linguistic Profile	Conduction	Conduction	Conduction	Conduction

The diagnosis made by these three judges and the interpretation made by ANN was compared to determine percentage of accuracy. Thereby providing objective evidence on efficiency of developed tool.

CHAPTER IV

RESULTS

The purpose of the present study was to create a model using an artificial neural network which could classify between individuals with and without aphasia and also differentiate between the aphasia subtypes

The following components of language abilities were taken up which constitutes the input data to the neural network.

Scores of the following subsections from the Western Aphasia Battery (WAB):

1. Fluency scores from the spontaneous speech section
2. Scores in Auditory Verbal comprehension section
3. Scores in Repetition section
4. Scores in Naming section

The data of 500 participants which included WAB scores of language components was subjected to stages of filtration to ensure quality input data as ANN input.

4.1 Results of Familiarity Check-1

This phase involved confirmation of diagnoses with the help of linguistic profiling and pre-diagnosed variants of aphasia. The task of the judges was to correlate the findings provided by them with the diagnostic label and decide if the label was highly agreeable, agreeable or less agreeable (on a three choice goodness rating). The cumulative results are as follows;

Table 8

Results of classification of aphasia variant post Familiarity Check-1

Aphasia Type	Goodness Rating			Confirmed diagnoses
	Highly agreeable	Agreeable	Less Agreeable	Percentage (%)
Global Aphasia	24	4	6	82.35
Broca's Aphasia	45	2	10	82.45
Transcortical Motor	7	2	4	69.23
Anomic Aphasia	18	3	6	77.77
Isolation Aphasia	5	0	2	71.42
Wernicke's Aphasia	25	1	8	76.47
Transcortical Sensory	7	3	3	76.92
Conduction Aphasia	21	5	4	86.66
Non- Aphasic	28	0	7	93.33

A total of 400 case files out of the total 250 met the criteria of either highly agreeable or agreeable on the goodness rating scale. Thus, 200 WAB scores were selected post the familiarity check 1.

4.2 Results of Familiarity Check-2

In the second type of familiarity check, the details on WAB, details on linguistic profiling of another 250 case files (extracted retrospectively as in the previous section) was given to three other judges (other than the one's participated in the previous type of familiarity check). The experience for the recruitment of judges remained the same as in the previous type. Here the task of the judges was to label the aphasia variant as per the standard classification. The cumulative results are as follows;

Table 9

Percentage classification of aphasia variant post Familiarity Check-II

Aphasia Type							
Global	**Broca's**	**TMA**	**Anomia**	**Conduction**	**Wernicke's**	**TSA**	**Non Aphasic**
14%	18.4%	3.2%	8%	11.6%	9.6%	4.4%	10.8%

80% of the total case files were confidently classified under one of the standardised aphasia classification variant.. Thus, 200 WAB scores were selected post the familiarity check II.

4.3 Phase I –Building and Training of ANN

4.3.1 Result of Building of ANN Phase

MATLAB version 8.5.0.197613 (The MathworksInc, R2015a) software was utilised for the study.

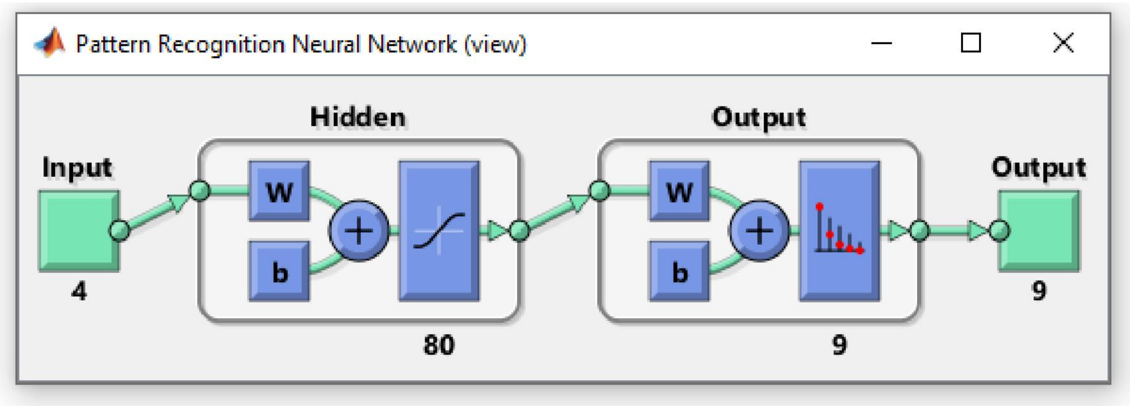

Figure 3: Pattern Recognition Neural Network Illustration

Using the Artificial Neural Network toolkit, a feed forward neural network was built. Optimal number error approach determined the properties of the ANN.

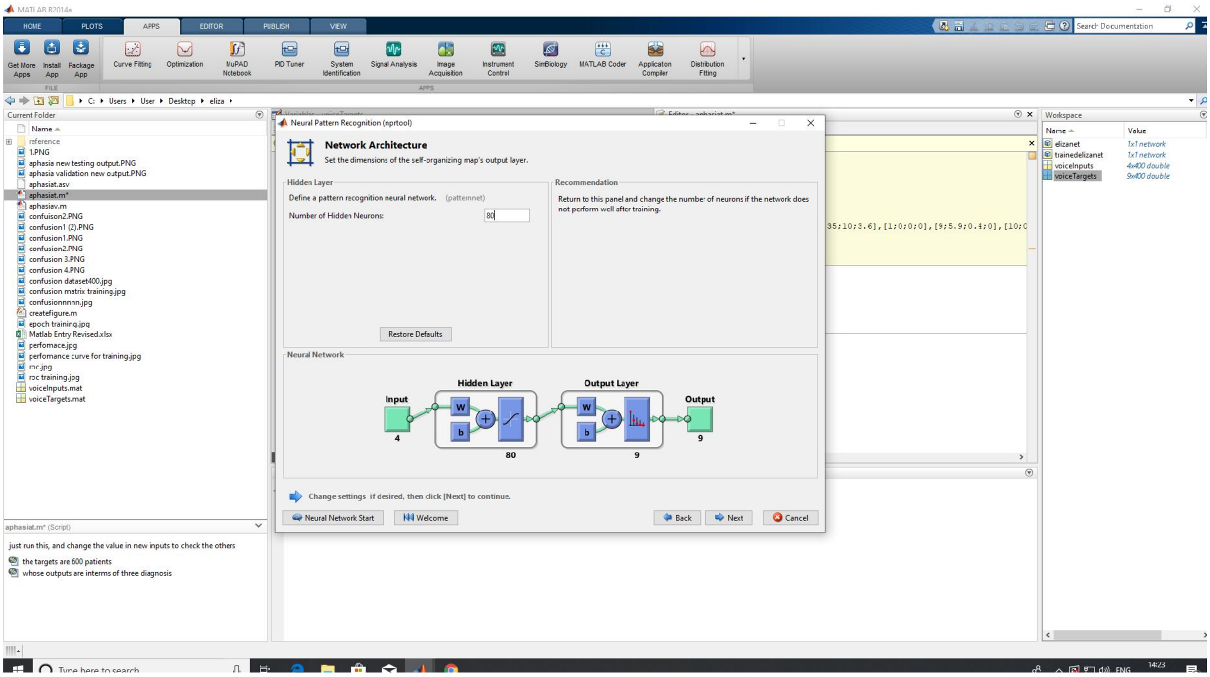

*Figure 4:*Sample of Network architecture construction on MATLAB

To avoid over generalization of the trained neural network the data was divided into two set, first was for model training (70%) by computing the gradient and revise the network and the second was for model testing (30%) for model testing using error validation.

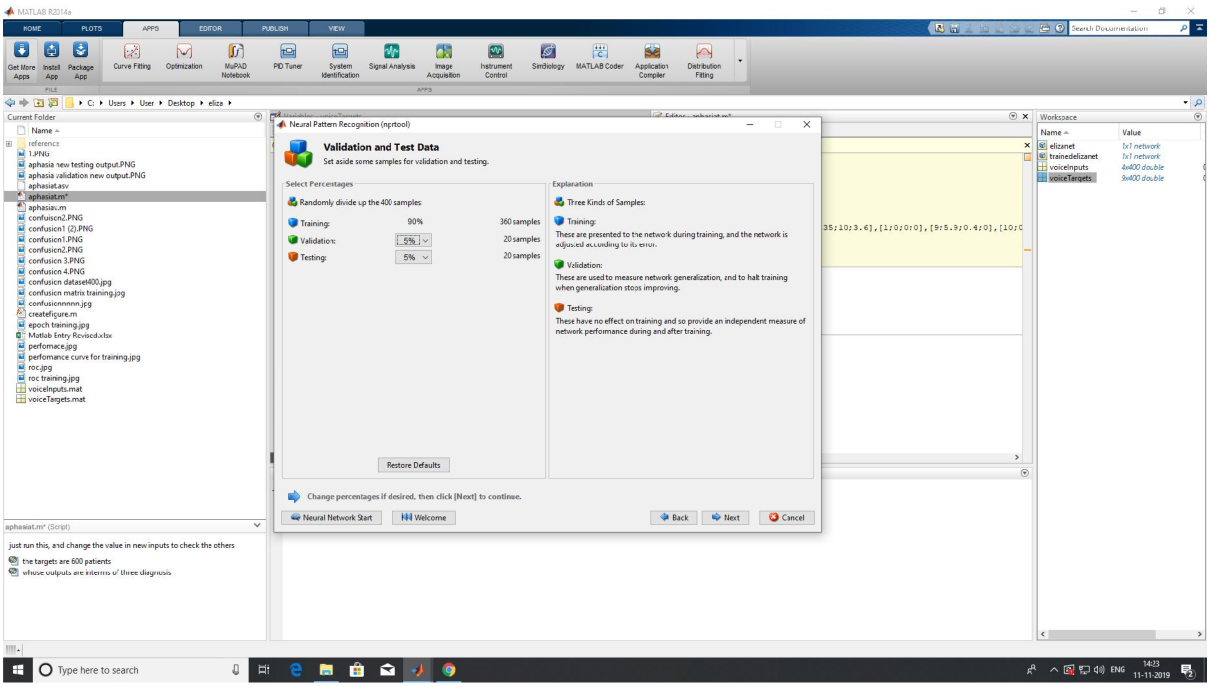

Figure 5: Sample of Validation and Test Input configuration on MATLAB

4.3.2 Results of Training of ANN Phase

4.3.2.1 Data Pre-processing phase

Before the parameters from the shortlisted case files post familiarity checks I and II could be fed into the neural network, a statistical analysis was done for each of the language parameters to find whether these parameters could significantly differentiate between persons with aphasia and those without.

The results of the different parameters have been discussed after analysing them using appropriate mathematical comparisons. The reference to the comparison has been derived from the clinical classification of aphasia (Kertesz,1982) and Boston Classification of aphasia characteristics.

Table 10

Cut off scores to determine the type of Aphasia (WAB, Kertez)

	Fluency	Comprehension	Repetition	Naming
Global	0-4	0-3.9	0-4.9	0-6
Broca's	0-4	4-10	0-7.9	0-8
Isolation	0-4	0-3.9	5-10	0-6
Transcortical Motor	0-4	4-10	8-10	0-8
Wernicke's	5-10	0-6.9	0-7.9	0-9
Transcortical Sensory	5-10	0-6.9	8-10	0-9
Conduction	5-10	7-10	0-6.9	0-9
Anomic	5-10	7-10	7-10	0-9

Table 11

Characteristics of different types of Aphasia (Boston classification)

Type of Aphasia	Fluency	Auditory Comprehension	Repetition	Naming
Global Aphasia	Non-Fluent	Poor	Poor	Poor
Broca's Aphasia	Non fluent, effortful, slow	Mild difficulty	Moderate-Severe	Moderate-Severe
Transcortical Motor	Non-Fluent	Mild	Good	Mid- Severe
Anomic Aphasia	Fluent	Mild	Mild	Moderate-Severe
Isolation Aphasia	Non fluent	Poor	Mild-Moderate	Poor
Wernicke's Aphasia	Fluent paraphasic	Defective	Mild- Severe	Moderate-Severe
Transcortical Sensory	Fluent	Poor	Good	Moderate-Severe
Conduction Aphasia	Fluent	Relatively good	Poor	Poor

Language Scores obtained after administration of Western Aphasia Battery

1. Fluency (subsection of Spontaneous Speech)

The examination of Table 12 revealed significant difference between non aphasic and aphasic fluency scores. (> significant of 0.05 level).

The non fluent variants of aphasia (Global, Broca's, TranscorticalMotor,Isolation) demonstrate means falling in the lower range i.e between 0-4. Similarly the fluent subtypes (Wernicke's, Transcortical Sensory, Conduction, Anomic) demonstrate mean scores within the higher range i.e between 5-10 (Table 11).

Table 12

The Mean, S.D and Range of Spontaneous Speech (Fluency) Scores for the different types of aphasia

Type of Aphasia	Mean	S.D	Range
Global Aphasia	0.6071	0.7305	0-3
Broca's Aphasia	1.7659	104695	0-4
Transcortical Motor	2.3333	1.5339	1-4
Anomic Aphasia	8.3333	1.2029	6-10
Isolation Aphasia	2.2	1.5491	1-4
Wernicke's Aphasia	7.3846	1.5861	5-10
Transcortical Sensory	7.2	1.8806	5-9
Conduction Aphasia	6.6470	1.4535	5-9
Non- Aphasic	10	0	10

2. Auditory Verbal Comprehension (AVC)

The examination of Table 13 revealed significant difference between non aphasic and aphasic auditory comprehension scores. (> significant of 0.05 level).

Table 13

The Mean, S.D and Range of Auditory Verbal Comprehension Scores for the different types of aphasia

Type of Aphasia	Mean	S.D	Range
Global Aphasia	2.0375	1.3572	0-3.9
Broca's Aphasia	7.1518	1.8364	4.1-10
Transcortical Motor	6.5722	1.3576	5-8.5
Anomic Aphasia	9.0921	0.8274	7-10
Isolation Aphasia	1.95	1.5806	0-3.6
Wernicke's Aphasia	3.6634	2.1841	0-6.85
Transcortical Sensory	4.61	2.3598	1-6.9
Conduction Aphasia	8.3539	0.9332	7-10
Non- Aphasic	9.4684	0.3412	9-9.8

3. Repetition

The examination of Table 14 revealed significant difference between non aphasic and aphasic repetition scores. (> significant of 0.05 level).

Table 14

The Mean, S.D and Range of Repetition Scores for the different types of aphasia

Type of Aphasia	Mean	S.D	Range
Global Aphasia	0.1651	0.4677	0-2.45
Broca's Aphasia	1.7122	2.0430	0-7.8
Transcortical Motor	9	0.9330	8-10
Anomic Aphasia	8.3023	0.8415	7-9.8
Isolation Aphasia	5.8	0.5416	5.2-6.4
Wernicke's Aphasia	1.6	2.0444	0-7.5
Transcortical Sensory	8.56	0.5528	8-9.4
Conduction Aphasia	3.3666	1.8403	0.2-6.9
Non- Aphasic	9.368	0.1965	9-9.6

4. Naming

The examination of Table 15 revealed significant difference between non aphasic and aphasic naming scores. (> significant of 0.05 level).

Table 15

The Mean, S.D and Range of Naming Scores for the different types of aphasia

Type of Aphasia	Mean	S.D	Range
Global Aphasia	0.2107	0.5610	0-2
Broca's Aphasia	2.3622	2.6489	0-8.2
Transcortical Motor	2.7111	1.7384	0-4
Anomic Aphasia	7.5785	1.4793	4.6-9.4
Isolation Aphasia	0.51	0.3754	0-0.9
Wernicke's Aphasia	2.9365	2.9973	0-9
Transcortical Sensory	4.22	2.0574	2.1-7.2
Conduction Aphasia	5.3647	2.1310	1.2-9
Non- Aphasic	9.6175	0.2071	9.3-10

The mean scores of the subtypes of aphasia for each of the language component are in concordance with the range of scores delineated in the manual of Western Aphasia Battery for the purpose of clinical classification of Aphasia.

Supporting literature classified in terms of aphasia variant documented below;

The conclusions drawn from the mean scores of language components in persons with Broca's aphasia are in line with the well known concept of Non-fluent telegraphic speech and reduced verbal content and phrase length). The same has been highlighted in terms of reduced fluency scores. Functional comprehension is present, but the patient has trouble following complex grammatical statements are confirmed by reduced than normal auditory verbal comprehension scores.

The mean scores in the case of the aphasia variant of Wernicke's aphasia highlights the phenomenon of Jargon speech Fluency, and paragrammatism. Severely impaired auditory comprehension is indicated by reduced scores in the auditory verbal comprehension subsection.

Mean scores associated with Conduction aphasia emphasize on the repetition defect. Relative fluency in spontaneous speech considerable word finding difficulty is indicated by the mean scores. Preserved auditory comprehension and significant difficulty with repetition are confirmed with the mean scores falling in the range as per the clinical classification of aphasia.

Word finding and naming Speech output is fluent with numerous pauses, pauses may be filled with circumlocutions, describing the function of an object; but the name cannot be retrieved. Such characteristics define Anomic aphasia. Auditory comprehension is intact. The same is also the conclusion drawn from the mean scores.

Patients with Global aphasia has been documented to display severe impairment in all modalities Speaking, listening, reading, and writing severely impaired. Auditory comprehension has been reported to be very limited. Speech output is limited only few understandable utterances. Low range scores and thereby leading to low mean scores in all language domain.

Transcortical motor aphasia displays characteristics similar to motor aphasia but with intact repetition. Non-fluent, limited speech output. Auditory comprehension is good. These characteristics are in accordance with the results obtained.

Conversely, Transcortical sensory aphasia is similar to sensory aphasia, but with intact repetition Deficits in all language modalities as in fluent aphasia demonstrated by the mean scores obtained in all language domains in the study.

4.3.2.2 Feeding Data into Neural Network

Post the pre-processing of data with the help of comparisons between all the subsections, the data was considered to be fed into the neural network , for processing and classification.

The data was trained using the Multi Layer Perceptron (MLP) Neural network model by using the data of 400 subjects. In order to obtain the best possible model to classify aphasia subtypes, the neural network was individually trained by adjusting the following parameters of the neural network (MLP).

1. The learning algorithms function of the neural network -The two learning algorithmic - Conjugate gradient and Levenberg-Marquardt - were taken up and the neural network was

trained in each of these algorithms to find which of the learning algorithm gave the best results.

2. The number of hidden layers - The network was trained with one and two hidden layers till eighty and it was calculated as to which option could give the best results.

3. The number of nodes in each hidden layer - The number of nodes in each hidden layer was adjusted sequentially from 1 to 20 in the case of the 1st hidden layer and 1 to 8 in the case of the 2nd hidden layer and so on.

The results indicated the following.

1. Using the learning algorithm 'Conjugate gradient' resulted in poor overall results when compared with the learning algorithm Levenberg-Marquardt.

2. By increasing the number of hidden layers to eighty, the neural network could classify the data samples more effectively than by using 1 hidden layer.

3. The best performance was obtained by using 6 nodes in the 1st hidden layer and 3 nodes in the 2nd hidden layer in and using 8 nodes and 3 hidden layers in the case of conjugate gradient.

By using 6 nodes and 3 nodes in the hidden layer in the learning algorithm of Levenberg-Marquardt the network model could correctly predict the aphasia variant by 85%, where as by using 8 nodes and 3 nodes in the 1st and 2nd hidden layers in the learning algorithm 'conjugate gradient' the network could correctly predict the aphasia variant only by 70.8%. Hence using the algorithm of Levenberg-Marquardt with 80 hidden layers was the best model which could classify normal subjects and subjects with aphasia with classification into its variants.

During the training phase a total of 400 data were trained. The neural net was designed to divide the total input in such a manner that 70% of the total date would be utilised for the training phase, the remaining 30% would be further divided into 20% and 10% for validation and testing phases respectively.

4.3.2.2 .1 Results of Training Phase by ANN

The results of the data in the training phase are given in the form of cross tabulation matrix as shown;

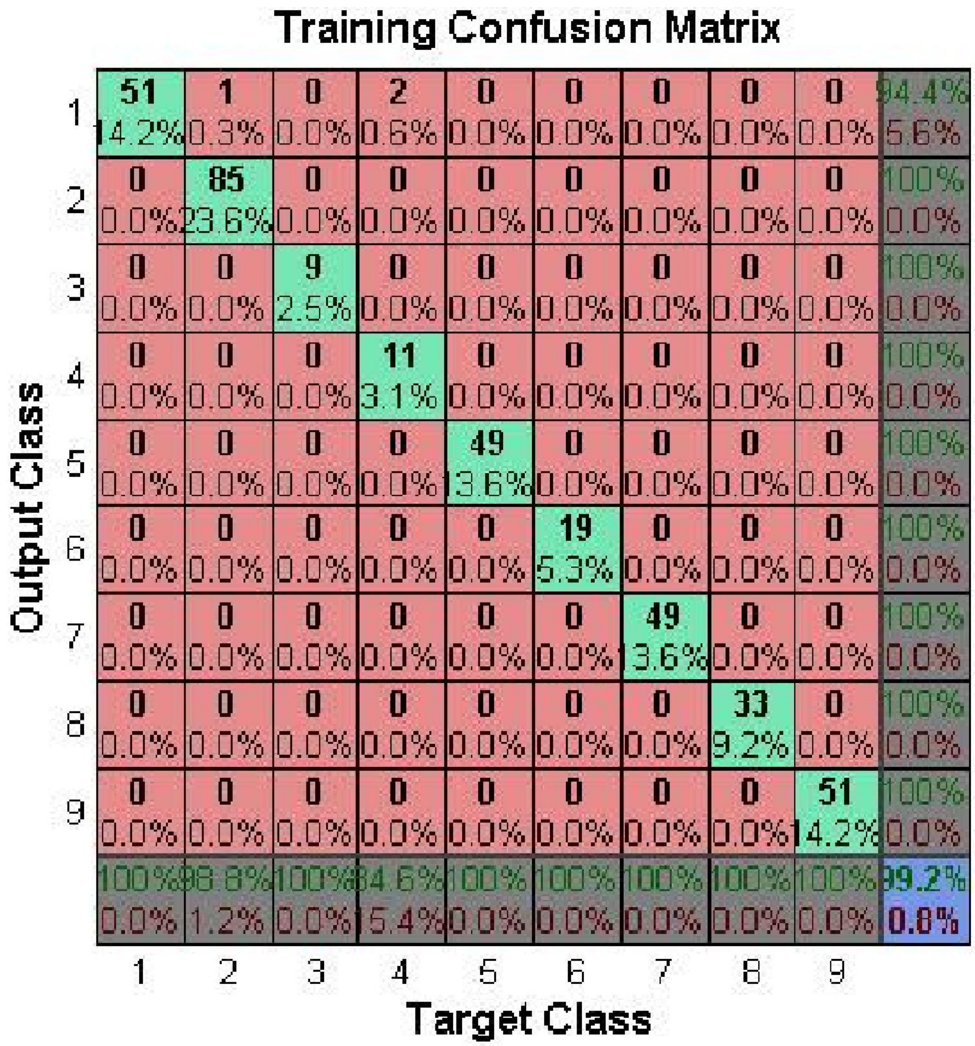

Figure 6: Confusion Training Matrix

Table 16

Percentage of the number of subjects identified correctly by the neural network by the Training Phase

Diagnosis	Total No. Of Samples	Samples Correctly identified	Percentage
Global Aphasia	54	51	94.4%
Broca's Aphasia	85	85	100%
Transcortical Motor	9	9	100%
Anomic Aphasia	11	11	100%
Isolation Aphasia	49	49	100%
Wernicke's Aphasia	19	19	100%
Transcortical Sensory	49	49	100%
Conduction	33	33	100%
Non- Aphasic	51	51	100%

On examination of the matrix, all variants have been classified as the intended classification category leaving global aphasia. There is a 94.4% accuracy identified in cases of global aphasia in the training phase. There has been a misdiagnosis of three samples into Broca's aphasia and anomic aphasia respectively which can be attributed to the closeness of scores in terms of Broca's variant and a comparative lack of training data for training in case of misdiagnosis into anomic aphasia. All other variants have proven to be diagnosed as per target classification categories.

In order to increase the accuracy of diagnosis, WAB scores of 10 patients with anomic aphasia was included at random and checked in subsequent training.

4.3.2.2 .2 Results of Validation Phase by ANN

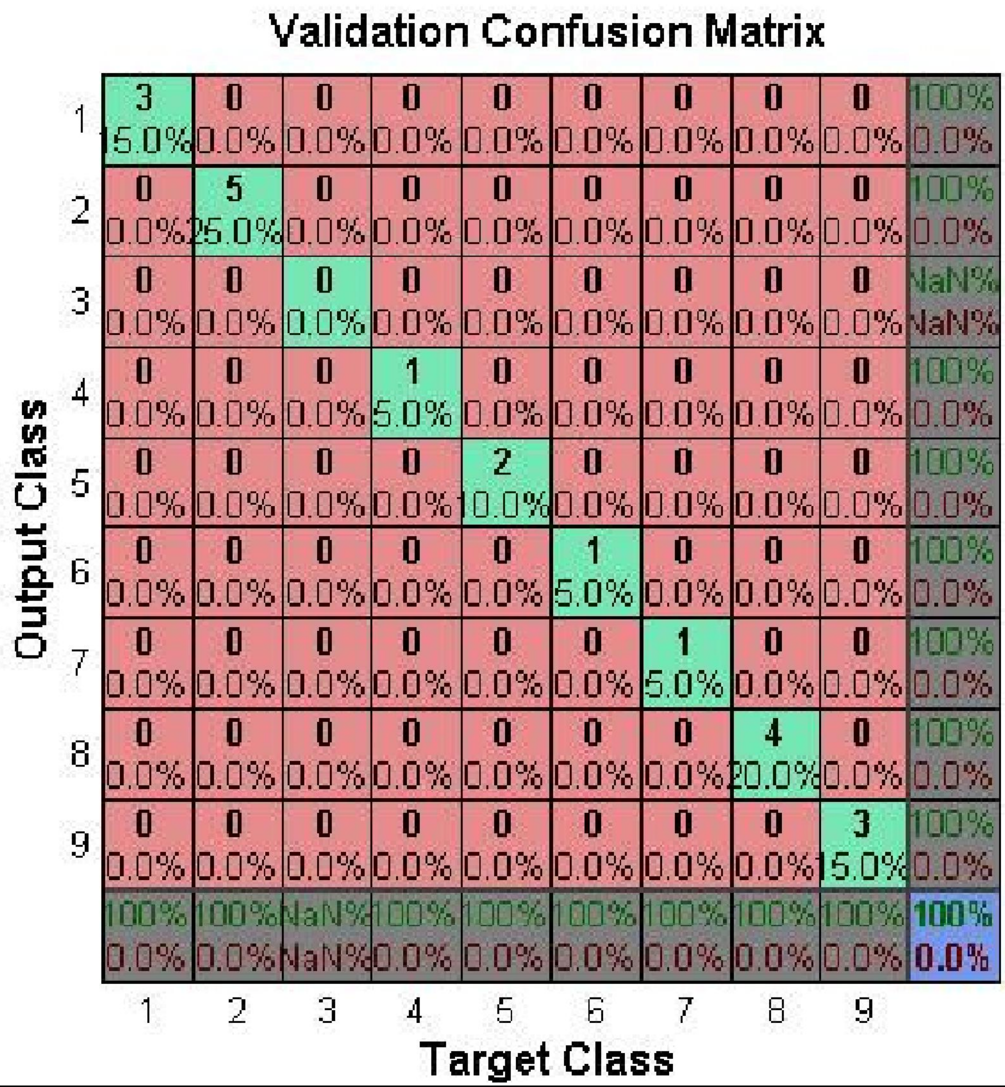

Figure 7: Validation Confusion Matrix

Table 17

Percentage of the number of subjects identified correctly by the neural network by the Validation Phase

Diagnosis	Total No. Of Samples	Samples Correctly identified	Percentage
Global Aphasia	3	3	100%
Broca's Aphasia	5	5	100%
Transcortical Motor	0	0	100%
Anomic Aphasia	1	1	100%
Isolation Aphasia	2	2	100%
Wernicke's Aphasia	1	1	100%
Transcortical Sensory	1	1	100%
Conduction	4	4	100%
Non- Aphasic	3	3	100%

On examination of the validation matrix, a 100% accuracy of diagnosis was found in the validation phase conducted by the ANN from the 70%-30% division carried out in the beginning phase.

4.3.2.2 .3 Results of Test Phase by ANN

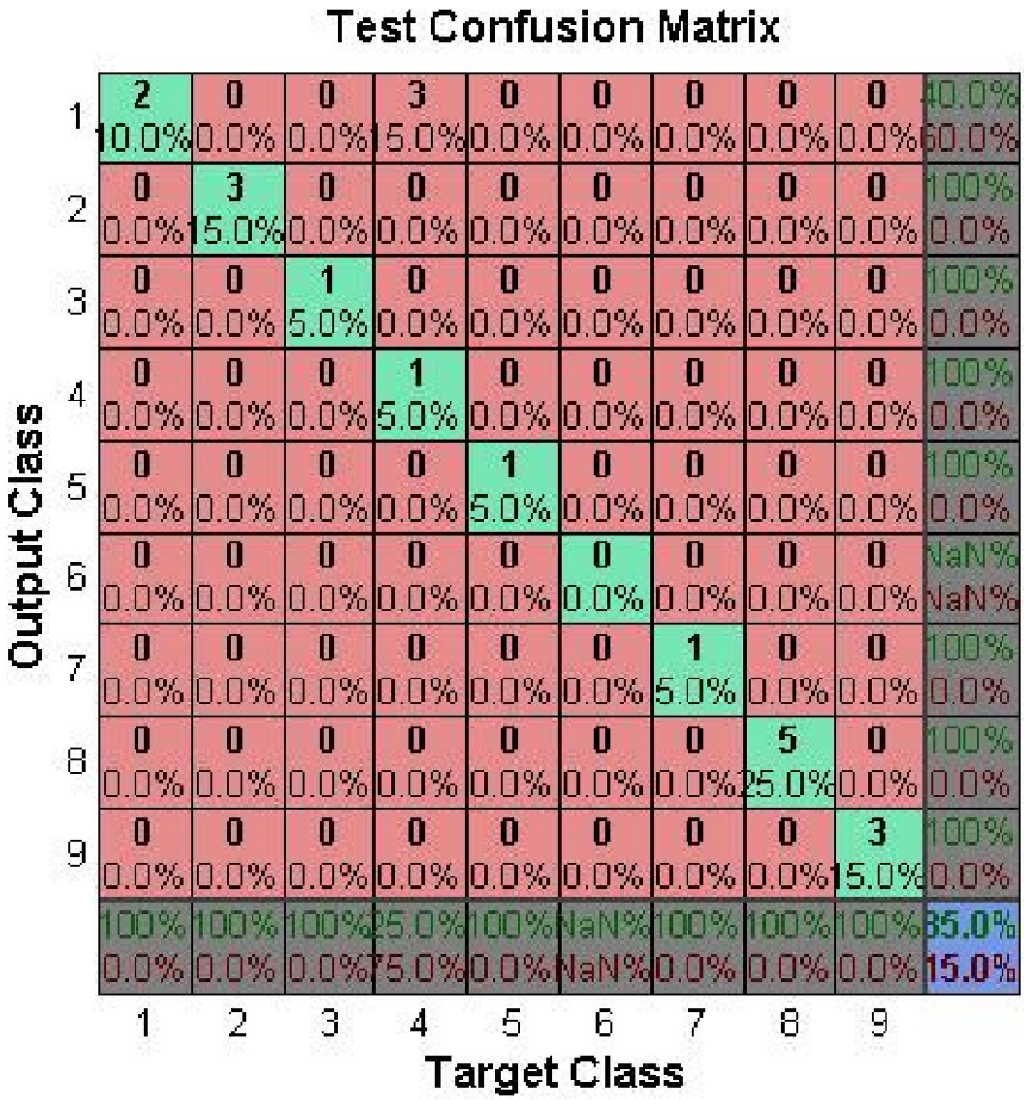

Figure 8: Test Confusion Matrix

Table 18

Percentage of the number of subjects identified correctly by the neural network by the Test Phase

Diagnosis	Total No. Of Samples	Samples Correctly identified	Percentage
Global Aphasia	5	2	60%
Broca's Aphasia	3	3	100%
Transcortical Motor	1	1	100%
Anomic Aphasia	1	1	100%
Isolation Aphasia	1	1	100%
Wernicke's Aphasia	0	0	100%
Transcortical Sensory	1	1	100%
Conduction	5	5	100%
Non- Aphasic	3	3	100%

In the final stage of phase 1, the ANN carried out a test phase using data from the 70%-30% division, an on examination of the matrix, a 100% identification of accurate diagnosis has been documented.

Since optimum results were obtained in the training phase, the developed tool was moved to the next phase in order to evaluate its efficiency in terms of new data input.

4.4 Phase II: Evaluating the efficacy of the ANN

The phase II involved introduction of new data which has not been previously used during the training in phase I. The new data included WAB scores of language domains belonging to 10 new patients who reported to the Institute clinic. The evaluation phase was carried out in two steps to ensure optimum performance.
The participants were evaluated by three SLPs in the first step and by the developed tool in the second step following which the results were compared.

4.4.1 Results of Evaluation by SLPs

Table 19

Classification of aphasia variant from new data by SLPs

Aphasia Type							
Global	**Broca's**	**TMA**	**Anomia**	**Conduction**	**Wernicke's**	**TSA**	**Non Aphasic**
1	1	1	1	1	1	1	2

The table depicts the diagnoses provided by the SLPs based on WAB scores and linguistic profile of the new data. As per the diagnoses, each variant received one type of aphasia and two non aphasic data was identified.

4.4.2 Results of Evaluation by ANN

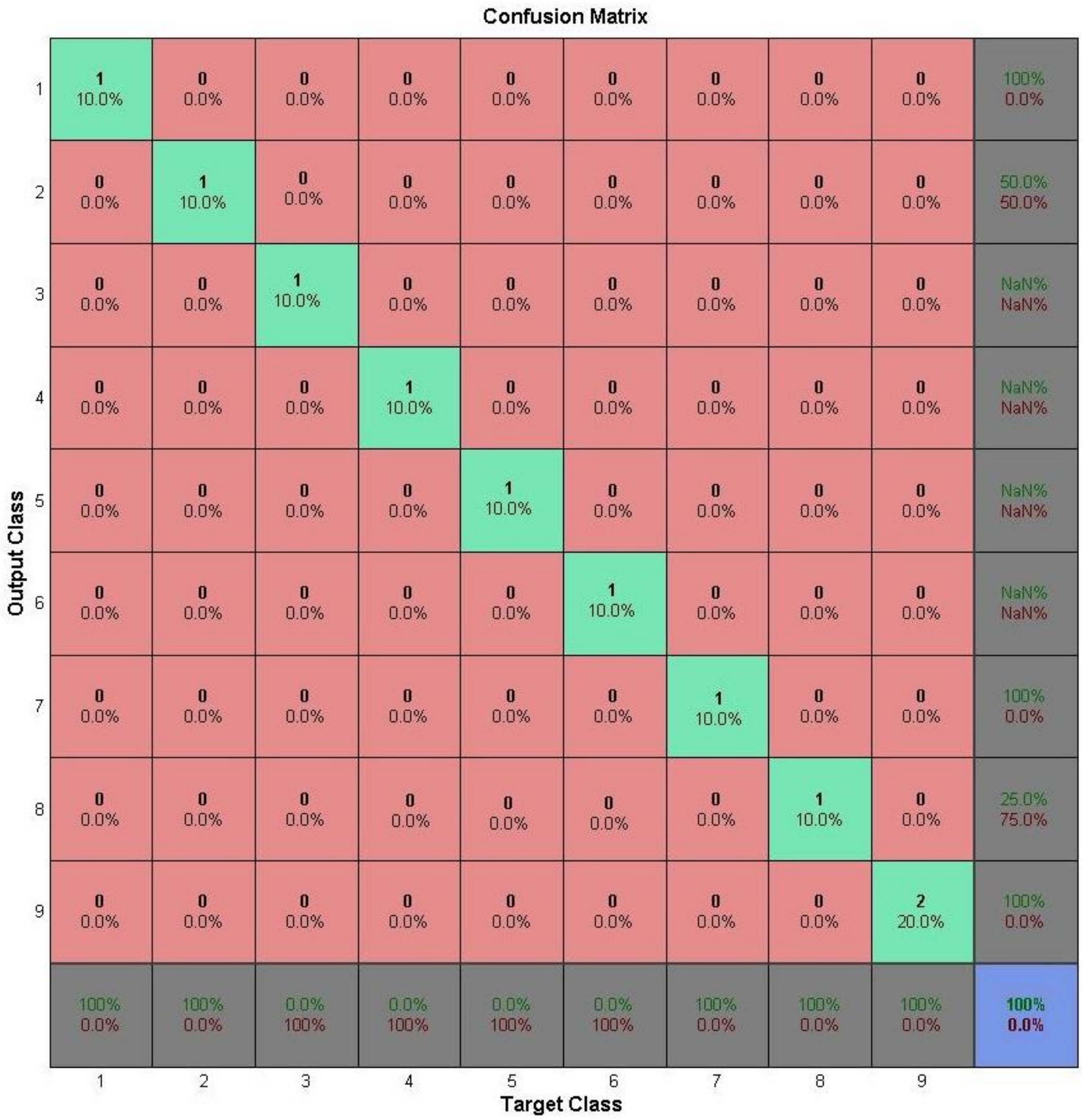

Figure 9: Confusion Matrix for Phase II (Efficacy of interpretation by developed tool)

Table 20: Percentage of the number if subjects identified correctly by the neural network by the Test for Efficiency Phase

Diagnosis	Total No. Of Samples	Samples Correctly identified by ANN (Diagnosis match with SLP)	Percentage
Global Aphasia	1	1	100%
Broca's Aphasia	1	1	100%
Transcortical Motor	1	1	100%
Anomic Aphasia	1	1	100%
Isolation Aphasia	1	1	100%
Wernicke's Aphasia	1	1	100%
Transcortical Sensory	1	1	100%
Conduction	1	1	100%
Non- Aphasic	2	2	100%

As mentioned earlier, step 2 included the process wherein the same data was provided as input to the developed tool and the matrix provides a detailed visual evidence of 100% accuracy on terms of interpretations having matched with those provided by the SLPs in step 1.

In order to confirm the interpretation provided in this phase, an additional crosscheck evaluation was carried out to ensure efficacy. The crosscheck phase included comparison of diagnoses by ANN with those by three SLPs and the results are tabulated below;

Table 21

Results of Crosscheck Evaluation by SLPs in Phase II

Diagnosis Method	**SLP 1**	**SLP 2**	**SLP 3**	**ANN**	**Percentage of Accuracy**
Global Aphasia	✓	✓	✓	✓	100%
Broca's Aphasia	✓	✓	✓	✓	100%
Transcortical Motor	✓	✓	✓	✓	100%
Anomic Aphasia	✓	✓	✓	✓	100%
Isolation Aphasia	✓	✓	✓	✓	100%
Wernicke's Aphasia	✓	✓	✓	✓	100%
Transcortical Sensory	✓	✓	✓	✓	100%
Conduction	✓	✓	✓	✓	100%
Non- Aphasic	✓	✓	✓	✓	100%

The percentage of accuracy was found to be 100% between the diagnoses by SLPs and the interpretation of data by the developed tool thereby confirming the efficacy of the tool.

To summarise, the results indicate a successful development of an Artificial Neural Network Tool for Aphasia classification using the framework of clinical classification in WAB (Kertez,1982). The pre processing of data revealed all four language domains (Fluency, Auditory Verbal Comprehension, Repetition, Naming) as significantly affecting the sensitivity of classification of aphasia. The training using 400 samples of WAB scores post two levels of compatbaility checks proved to be efficient in diagnosing aphasia variant. This was tested for efficacy via validation, testing and cross check methods using new WAB scores. The results of the mentioned evaluation have confirmed 100% accuracy.

CHAPTER IV

DISCUSSION

The famous Martin H. Fischer quotes 'Diagnosis is not the end, but the beginning of practice.' This principle not only applies to medical diagnosis alone but also to every interpretation provided in the field of communication sciences. The accuracy and confidence of diagnosis is crucial to plan rehabilitation and document the progress. The mentioned purpose becomes crucial in treatment of adult population who most commonly are the victims of language loss after having led a perfectly normal life, as in Aphasia. The need to accurately diagnose and plan an effective treatment approach becomes crucial for reintegration of the individual and to ensure Quality of life and Life Satisfaction on the whole.

Literature reports of use of technology as being the cutting edge need and research interest of scientists working to develop inventions in the medical field fraternity. The concept of tele practise of medicine and medial consultation finds its roots as initial attempts to integrate technology into medicine.

The use of Artificial Intelligence in the field of medical diagnosis has been gaining popularity. Literature reports of use of neural network based prediction of cancers along with gene expression profiling(Khan, J., Wei, J.S., Ringner,M., Saal,L.H., Ladanyi, M., Westermann,G et al., 2001), classification of relapsing remitting multiple sclerosis (Fooladi, M., Sharini,H., Masjoodi,S., Khodamoradi,A., 2018), analysis of psychiatric disorders (Galletly, C., Clark,R., McFarlane, A., 1996), detangling heterogeneity in schizophrenia (Bosia,M., Bechi, M., Francesaca, B., et al., 2018), applications in urology (Wei, J., Chang., Barnhill, A., &Oesterling, J., 1998). The review reveals appreciable and promising results in the medical field utilised. The authors report inclusion of large data as input samples and inclusion of variety of possible outcomes for best prediction as results. The incorporation of neural networks has exceedingly aided in the diagnosis, prognosis and survival analysis of various medical conditions. It has accelerated the identification and early intervention of cancer and other degenerative disorders. It has provided a ray of hope to curb preventable diseases by identifying them at a stage when they are treatable with zero percent relapse.

Looking specifically into the field of communication sciences, technology has brought about the increasing use of machine learning techniques in classification of disorders associated with speech-language and hearing sciences. For instance, the published reports of dyslexic classification (Miikkulainen, R., 1997) reports of successful attempt to simulate dyslexic errors. Attempts in understanding speech intelligibility from acoustic variables (Metz, D., Schiavetti, N., Knight, S., 1992) provided preliminary data for its classification. Pathological voice quality assessment is one such area which has been extensively studied and findings support promising results (Ritchings, R., McGillion, M., Moore,C., 2002). Classification of Parkinson's disease has been attempted by researchers using ANNs and results have provided finely tuned neural networks with high test accuracy (Berus, L &Ficko, M). The review suggests presence of significant attempts to incorporate the use of machine learning in the clinical diagnosis of pediatric as well as adult communication disorders. Aphasia is one such language impairment which has received attention in the recent past in the light of artificial neural networking. However the research has been limited to the causes and symptoms of the stroke which resulted into condition such as Aphasia (Halai, A., Woollams,A& Ralph, L., 2018). This dearth in understanding of clinical expression of aphasia encouraged the need to the study in discussion.

Aphasia being an acquired language impairment with various subtypes presents in itself as a challenging task towards diagnosis and subsequent treatment planning. A successful intervention can only be executed when the the deficits are precisely identified and labelled.

Aphasia, due to its complex nature, has received several contradicting views regarding the need to classify its variants. However, the investigating diagnosticians have considered the diagnosis as a potential means to objectively report the aphasia subtype and allow systematic documentation of progress if administered periodically.

The study has resulted in the creation of an effective tool towards classification of aphasia subtype on the lines of clinical classification of the Western Aphasia Battery (WAB). The input to the data after pre processing was identified to be all domains of language and hence fluency, auditory comprehension, repetition and naming scores were included in the input sets. The data pre processing phase has been utilised in previous studies involving neural networks in order to identify variables leading to significant alterations in the output (Binu, 1998).The tool which was developed as part of the project in its first stage with less than targeted number of samplesyielded unsatisfactory results. This can be attributed to the unequal input of types of variants of aphasia and the limited availability of specific type of aphasia (ex-Isolation Aphasia). Therefore the samples size was increased to four hundred to receive efficient training. The ANN has the ability to self validate the input data and then run a test phase to ensure its efficiency. The ability of the network to conduct validation and test phases depicts the accuracy of analysis and its objectivity in the beginning stage itself. Such validation and testing phases allow revisions of the training of the network to improve the accuracy of output by reducing error. As a result of this feature, the study has proven satisfactory in terms of accurate classification which led its advancement into the next level of testing.Additional test retest measures were employed to assess efficiency of the tool. The verification by experienced professionals is a method utilised very minimally in the literature to support the classification of the ANN. Thereby allowing the current study to have double verification in terms of validity and accuracy of output.

Therefore, the current study is first of its kind to have utilised the amalgamation of technology , in terms of Artificial Intelligence and communication sciences, Aphasia in particular. The developed tool allows objectivity and provides confidence to novice diagnosticians to incorporate the application of artificial neural networking into aphasia diagnosis with no evidence of vagueness.

CHAPTER V

SUMMARY AND CONCLUSION

The study was conducted broadly in two phases; Phase I involved data collection, its verification, development of Artificial Neural Network based Tool on MATLAB and the training of the developed tool. Subsequently Phase II involved the efficacy analysis of the developed tool by introduction of new data.

In detail, Phase I was initiated was identifying, retrospectively, potential cases with an aphasia diagnosis at various clinics and institutes. The identification involved filtration of case files of patients who reported with language disturbances post stroke and a subsequent diagnosis of Aphasia. A total of 500 case files were identified which were subjected to two types of familiarity checks. Familiarity check 1 involved agreement analysis of the diagnosis by three experienced speech language pathologists. This check allowed selection of 200 case files after filtration. Familiarity check 2 involved selection of case files based on details of WAB and linguistic profiling conducted by three speech language pathologists (other than the one's participated in the previous type of familiarity check). The familiarity check 2 identified the case files meeting the majority criterion by the SLPs and resulted in the identification of a total of 400 case files in total.

This was followed by development of the tool. Using the Artificial Neural Network toolkit, a feed forward neural network was built. Optimal number error approach was used to specify the maximum number of training epochs, learning rates, number of nodes in a hidden layer. To avoid over generalization of the trained neural network the data was divided into two set, first was for model training (70%) by computing the gradient and revise the network and the second was for model testing (30%) for model testing using error validation.

The WAB scores of language domains from the identified 400 case files were loaded on to the developed tool and analysed through training, validation and testing stages by the neural network. Each stage provided results which allowed necessary modifications to be made in the programming to enhance efficiency. Finally, by the end of phase I, optimum results were obtained in the training phase and the developed tool was moved to the next phase in order to evaluate its efficiency in terms of new data input.

In phase II, new data was introduced which included WAB scores of language domains belonging to 10 new patients who reported to the Institute clinic. The patients were independently diagnosed by speech language pathologists and interpreted by the developed tool respectively.

A 100% accuracy was obtained in the efficiency testing phase. In order to ensure no room for false positive results, the results were subjected to a final stage of confirmation. This involved a cross check evaluation by three independent speech language pathologists working in the field of adult language disorders. The diagnoses provided by each was compared to that with provided by the developed tool and the results have been found to be promising.

The present study aimed to build an objective tool that assists professionals in deriving an objectivity at classification of various aphasiac symptoms. The present study was a first of its kind to derive a confidence index that could highlight on the recovery period of aphasiac symptoms and thereby guide in choosing appropriate intervention strategies. Results of the present study have revealed good agreement between the traditional standardized test scores and the results of the developed tool. The premise for these findings was nonlinearity and the generalization of the ANN in the training phase. This tool can help guide novice diagnosticians in decision making as well as planning appropriate intervention strategies. Further studies are required to evaluate its effectiveness on a larger audience and make this tool a universal tool. Hence making it to be an easy to use assistive tool that guides professionals in the complex task of diagnosis and intervention planning of persons with aphasia.

5.2 Implications of the study

1. The study used a neural network which has a capability to learn and understand complex data and hence creates an objective classification model for Aphasia.

2. Such applications can be attempted into other speech and hearing disorders. This can be used for a regular clinical activity.

5.3 Limitation

1. The numbers of subjects were not uniformly distributed in terms of type of Aphasia.
2. The participants were not classified on the basis of duration post onset of aphasic symptoms.

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