CLASSIFICATION ON DEGREE OF HARMING IN PARKINSON DISEASE

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Abstract: Machine learning is set of methods which can detect pattern in data, create new pattern, and can estimate future data. There are mainly two types of machine learning supervised and unsupervised. Neural network is technique of machine learning which is used for perposed work. As we have seen that nowadays many neurological disorder problems found in every age group. From these neurological disorders Parkinson disease is gradually increasing in older people. It has generally seen after the age of 50. Symptoms of Parkinson disease seems similar to other neurological disorders at the first time, thats why sometime it is difficult to differentiate it from other neurological disorders. This disease reduce the quantity of dopamine in the substantia nigra,in the part of brain. Dopamine helps to carry signals from brain to all parts of body. When degree of dopamine decreases in brain body movements becomes slow. Its symptoms are generally muscle stiffness, shaking, lower balance of body, and voice distortion. We choose the voice distortion for our research because if person is affected with PD it can be easily identified from its vocal speech. Parkinson disease patient's voice would be harsh,rigid and sometimes he cannot pronounce words properly. There are many diagnosis system have been developed for Parkinson disease but these systems can only classify it into two stages healthy or unhealthy. So we have tried to classify it into more then two stages so that diagnosis can be more easy. We classify it into 7 stages which shows the degree of harming from his speech signals. We use ANN based stage classifier, we calculate the features then perform pre-processing then classify it. Our result for this research work is shows 88.9% accuracy in true classification of data in seven different stages of the disease.

1. INTRODUCTION

Neurological disorders, including Parkinson's disease (PD), Alzheimer's, and epilepsy, profoundly affect the lives of patients and their families. PD affects over one million people in North America alone. Moreover, an aging population means this number is expected to rise as studies suggest rapidly increasing prevalence rates after the age of 60. In addition to increased social isolation, the financial burden of PD is significant and is estimated to rise in the future. Currently, there is no cure, although medication is available offering significant alleviation of symptoms, especially at the early stages of the disease. Most people with Parkinson's (PWP) disease will therefore be substantially dependent on clinical intervention. For many PWP, the requisite physical visits to the clinic for monitoring and treatment are difficult. Widening access to the Internet and improved telecommunication systems band width offer the possibility of remote monitoring of patients with substantial opportunities for lowering the inconvenience and cost of physical visits. However, in order to exploit these opportunities, there is the need for reliable clinical monitoring tools. Research has shown that approximately 90% of PWP exhibit some form of vocal impairment [2], [3]. Vocal impairment may also be one of the earliest indicators for the onset of the illness [5], and the measurement of voice is noninvasive and simple to administer. Thus, voice measurement to detect and track the progression of symptoms of PD has drawn significant attention [7], [8].

Symptoms of neurological disorders
PWP typically display a constellation of vocal symptoms that include impairment in the normal production of vocal sounds (dysphonia) and problems with the normal articulation of speech (dysarthria). Dysphonic symptoms typically include reduced loudness, breathiness, roughness, decreased energy in the higher parts of the harmonic spectrum, and exaggerated vocal tremor. There are many vocal tests that have been devised to assess the extent of these symptoms. These include sustained phonations [10], [11], where the patient is instructed to produce a single vowel and hold the pitch of this as constant as possible, for as long as possible, and running speech tests [11] where patients are instructed to speak a standard sentence constructed to contain a representative sample of linguistic units. Several of these tests may need to be administered for a full assessment of vocal impairment, but any symptom is sufficient for detecting the severity of PD. Although running speech might be considered a more realistic test of impairment in actual everyday usage, simple sustained phonation tests are able to elicit dysphonic symptoms, and tests of the effectiveness of measurements for detecting dysphonia are best conducted without the confounding effects of articulatory or linguistic components of running speech. Therefore, in this study, we will concentrate on sustained phonation tests.

There have been extensive studies of speech measurement for general voice disorders [1], and PD in particular [13]. Speech sounds produced during standard speech tests are recorded using a microphone, and the recorded speech signals are subsequently analyzed using measurement methods (implemented in software algorithms) designed to detect certain properties of these signals. The main traditional measurement methods include F0 (the fundamental frequency or pitch of vocal oscillation), absolute sound pressure level (indicating the relative loudness of speech), jitter (the extent of variation in speech F0 from vocal cycle to vocal cycle), shimmer (the extent of

variation in speech amplitude from cycle to cycle), and noise-to-harmonics ratios (the amplitude of noise relative to tonal components in the speech) [10]. Studies have shown variations in all these measurements for PWP by comparison to healthy controls [14], indicating that these could be useful measures in assessing the extent of dysphonia. More recently, a variety of novel measurement methods have been devised to assess dysphonic symptoms, in particular, those based on nonlinear dynamical systems theory [15]. These measurements are motivated by extensive modeling studies [16] and evidence [17] that vocal production is a highly nonlinear dynamical system, and that changes caused by impairments to the vocal organs, muscles, and nerves will affect the dynamics of the whole system. As a result, these changes can be detected by nonlinear time series analysis tools [6], such as correlation dimension and methods for characterizing pseudoperiodic time series [18], [19]. Similarly, randomness and noise are inherent to vocal production [1]; as a result, tools such as recurrence period density entropy (RPDE) and detrended fluctuation analysis (DFA) have been applied to speech signals, showing the ability to detect general voice disorders [1].Nonetheless, practical, remote assessment of dysphonia requires high reliability, and this is impeded by several confounding issues. Sound recording and measurement methods will differ in robustness to uncontrolled variation in the acoustic environment of the clinic and home and to the physical condition and characteristics of the subject. In order to gain as much reliability as possible, measurement methods should be chosen that are as robust as possible to such uncontrolled (and in many cases, uncontrollable) variations. For example, absolute sound pressure-level measurement requires costly calibration equipment, and the requisite precision is often difficult to obtain. This limits the reliability of this measure in telemedicine applications. correspondingly, while PD-related dysphonia is related with decrease absolute speech F0, this is confounded by unrelated effects such as individual preferences or subject gender [13].

2. RELATED WORK

In this paper they introduce a novel approach for recognizing PD utilizing mind MRI checks. As a result of non-obtrusiveness and high determination property, MRI is favored over different strategies. For this investigation, the MRI pictures (sound/PD patients) have been gathered from Parkinson's Progression Markers Initiative (PPMI) association. Research endeavors have expressed that Extreme Learning Machine (ELM) has better and precise finding capacity. In this paper, PD analysis in view of ELM-based strategy alongside Genetic Algorithm highlight subset choice has been proposed. The classifier utilizes voxel based morphometric highlights separated from MRI. Since, the element separated are substantial in number, an element subset choice strategy utilizing Genetic Algorithm is executed. The execution of GA-ELM strategy is assessed utilizing order precision, affectability, specificity. The outcomes demonstrate that the arrangement precision acquired for ELM display is higher than the one got utilizing SVM approach. Additionally GAELM classifier demonstrate produces a superior speculation execution with high affectability and low misclassification rate.

Parkinson's disease is a progressive neurodegenerativedisorder. Risk of Parkinson disease increases with the age of person, most probably it occurs after the age of 50. so it is generality spreading in those countries in which length of life of the person is increasing. Cerebral complications are general in Parkinson disease and diagnose those problems is an essential field of research. In this paper they analyze the latent for using objective, automated methods basedaround asimple figure copying exercise administered on a graphics tablettopeople with Parkinson's disease. For this they use a multiobjectiveevolutionary algorithm to analyze a capacity of regressionmodels and these modelsproduce a combination of features derive from a patient's digitized drawing. This access is adapted to review the predictive regression models that capture a patient's degreeof motor and cognitive dysfunction and the results of this access shows that analytic ratio of motor and Cerebral decline can be predicted, even ifchanging degree within distinctive patient subpopulations. From modeling point of view linear models presents to be higherguessing in contrast to polynomial models [12].

Festinating gait is generally seenmotor syndrome of Parkinson's Disease patients. In this analysis the nature of festinating gait is observed through an accelerometer-based sensing system which is actualize on a vest. The disclosurealgorithm is based on theanalysis of gait similarityfrom the data measured byaccelerometers. Clear-cut indications were scheduled to check the sharpness of festinating gait nature. This system disclose the upper body lean ahead slant whilewalking, as well as it could be used for long-term course monitoring tool for the progress of festinating gait. This tool support users to see the enlargement of the radical nature of festinating gait and to have good medication onPD earlier. In the proposed system a step symmetry index on gait pattern is presented for the detection of fast shuffling footsteps. The single and double-side fast shuffling footstep can be recognized using average and standard deviation of step symmetry [2].

Voice destruction study has been used as an productive mechanism for initial detection of Parkinson's disease (PD). This paper describe an powerful way to forecast Parkinson's disease accurately using voice samples with Extreme Learning Machine. This system is compered with reliable dataset from UCI repository. The efficiency of this system is 90.76% for differentiate between Parkinson diseased subjects and healthy subjects and 0.81 MCC for the training dataset. This technique is also compared with existing techniques like Neural Network and Support Vector Machine and results shows that this method is reliable for diagnose the Parkinson's disease. The given system is an powerful approach to achieve an specific predictive model for telemonitoring of Parkinson's disease using Extreme Learning Machine (ELM). To identify PD subjects accuracy of the system is 81.55%. This study depicts that constant vowels give ample clue to forecast Parkinson's disease. It is a reliable model because of its simple construction and built in learning of the data [4].

In this paper different ways to diagnosis of Parkinson's disease at its initial state using voice are described. Main motive of this research is to give a good working and economical system for the detection of Parkinson's disease. As we know there is no cure for PD and existing therapies

are highly priced for PD. These therapies may give little bit peace to the patients and help them to improve their quality of life. Our speech carry various features which have essential disparty between healthy people and Parkinson's patient such as pitch, jitter shimmer, Mel-frequency Cepstral Coefficient (MFCC), glottal pulse and formant. All these features are diagnosis and tested for healthy and PD patients [5]. According to this analysis:

1. The pitch of PD patient is higher then normal person in males.

2. Normal person have less Formants disparty fr.om PD patients

3.Normal persons have less jitter and Shimmer values as compared to PD patients [5].

As we know there is no cure for Parkinson's Disease, patients need to attend reclamation programs continuously, so that they can attain good of life. But at some point they got bored from this process and give up. Exergames is a program in which character-based, virtual reality exercises are provided in the form of games and these games engage players to train in a non-linear mode by giving them training which varies from one game loop the next. This game carry a number of gestures drawn from current PD special training schedule that advocate big and purposive action, meant to better postural balance and reflexes as well as improve the global movability of upper and lower limbs. When limbs movements of patient match with the programmed gesture, a 3D cartoon avatar behave respectively. Conclusively, this game decision making wish to enhance patient's cognitive reaction. An exergame is designed and developed clear for PD patients with warm to gentle motor symptoms to practice on their own [6].

3. RESEARCH METHDOLOGY

Data used

The information for this examination comprise of 195 managed vowel phonations from 31 male and female subjects, of which 23 were determined to have PD. The time since analyze ran from 0 to 28 years, and the times of the subjects extended from 46 to 85 years (mean 65.8, standard deviation 9.8). Midpoints of six phonations were recorded from each subject, extending from 1 to 36 s long. See Table I for subject points of interest. The phonations were recorded in an Industrial Acoustics Company (IAC) sound-treated stall utilizing a head-mounted mouthpiece (AKG C420) situated at 8 cm from the lips. The mouthpiece was aligned as portrayed in [13] utilizing a class 1 sound-level meter (B&K 2238) set 30 cm from the speaker. The voice signals were recorded specifically on PC utilizing Computerized Speech Laboratory (CSL) 4300B equipment (Kay Elemetrics), tested at 44.1 kHz, with 16-bit determination. In spite of the fact that sufficiency standardization influences the alignment of the examples, the investigation is centered around measures obtuse to changes in supreme discourse weight level. Along these lines, to guarantee power of the calculations, all examples were carefully standardized in sufficiency preceding computation of the measures[14].

TABLE 1: List of subjects with sex, age, parkinson's stage, and number of years since diagnosis

Subject Code	Sex	Age	Stage	Year Since Diagnosis
S01	M	78	3.0	0
S34	F	79	2.5	1/4
S44	M	67	1.5	1
S20	M	70	3.0	1
S24	M	73	2.5	1
S26	F	53	2.0	$1\frac{1}{2}$
S08	F	48	2.0	2
S39	M	64	2.0	2
S33	M	68	2.0	3
S32	M	50	1.0	4
S2	M	60	2.0	4
S22	M	60	1.5	$4\frac{1}{2}$
S37	M	76	1.0	5
S21	F	81	1.5	5
S04	M	70	2.5	$5\frac{1}{2}$
S19	M	73	1.0	7
S35	F	85	4.0	7
S05	F	72	3.0	8
S18	M	61	2.5	11
S16	M	62	2.5	14
S27	M	72	2.5	15
S25	M	74	3.0	23
S06	F	63	2.5	28
S10(Healthy)	F	46	N/A	N/A
S07(Healthy)	F	48	N/A	N/A
S13(Healthy)	M	61	N/A	N/A
S43(Healthy)	M	62	N/A	N/A

S17(Healthy)	F	64	N/A	N/A
S42(Healthy)	F	66	N/A	N/A
S50(Healthy)	F	66	N/A	N/A
S49(Healthy)	M	69	N/A	N/A

Entries labeled "n/a" for healthy subjects for which Parkinson's stage and years since diagnosis is not applicable. "H&Y" refers to the Hoehn and Yalr- PI) stage, where higher values indicate greater level of disability [2].

Classification by neural network

Artificial Neural Network (ANN) [19] has been the successfully used classifier in numerous fields. It can be modeled on a human brain. The basic processing unit of brain is neuron which works identically in ANN.

The neural network is formed by a set of neurons interconnected with each other through the synaptic weights. It is used to acquire knowledge in the learning phase. The number of neurons and synaptic weights can be changed according to desired design perspective. The basic neural network consists of 3 layers.

- *Input layer*: The input layer consists of source nodes. This layer captures the features pattern for classification. The number of nodes in this layer depends upon the dimension of feature vector used at the input.

- *Hidden layer*: This layer lies between the input and output layer. The number of hidden layers can be one or more. Each hidden layers have a specific number of nodes (neurons) called as hidden nodes or hidden neurons. The hidden nodes can be varying to get the desired performance. These hidden neurons play a significant role in performing higher order computations. The output of this layer is supplied to the next layer.

- *Output layer*: The output layer is the end layer of neural network. It results the output after features is passed through neural network.

The arrangement of yields in yield layer chooses the general reaction of the neural system for a provided input highlights.
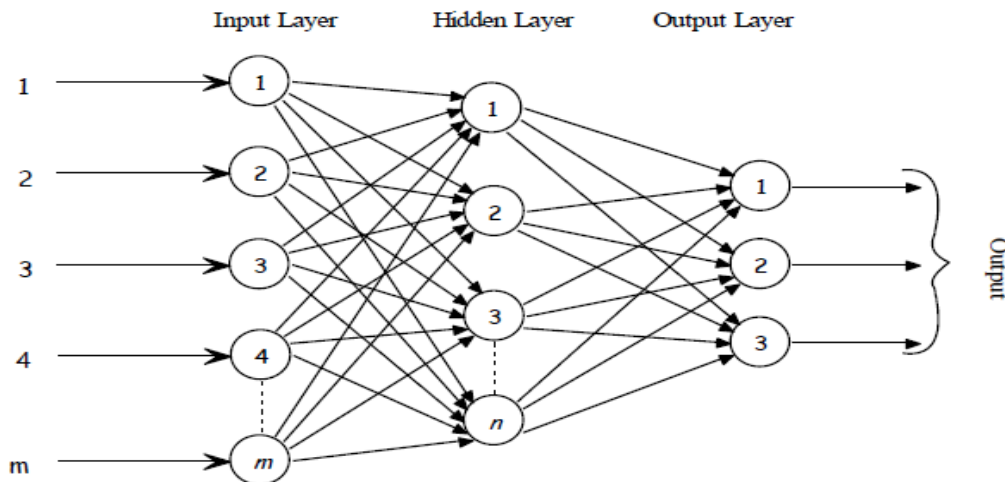

Figure 1: General Structure of a Neural Network

Input Pattern

Typically many input/target pairs are needed to train a network. For this purpose the training, testing and their corresponding target patterns were made using feature vectors. Various features that have been extracted acts as an input pattern for neural network. Thereafter the input data were normalized by subtracting the mean and dividing by the standard deviation to ensure that the distance measure accords equal weight to each variable; i.e. all values of attributes in the database are changed to contain values in a definite range (-1, 1). Without normalization, the variable with the largest scale can dominate the measure.

Target Pattern

In this work the target vector was encoded using one hot encoding method. One-hot refers to a group of bits among which the legal combinations of values are only those with a single high (1) bit and all the others low (0). For example, the output of a decoder is usually a one-hot code. Table 3.1 displays the plant classes and their corresponding target vectors in one hot encoded form.

Table 2 Target pattern Encoding

S.No	Stages of PD	Target Pattern
1	stage 1	1000000
2	stage 2	0100000
3	stage 3	0010000
4	stage 4	0001000
5	stage 5	0000100
6	stage 6	0000010

| 7 | stage 7 | 0000001 |

Architecture Design of MLP Classifier.

The feed-forward neural network (FFNN) [19] is the most popular classifier. In this work MLP-FFNN classifier is being used. Their main advantage is that they are easy to use, and that they can approximate any input/output mapping with weights and thresholds (biases) of the model. Tackling a non-linear classification problem, like PD classification, requires a neural network with at least three layers of neurons,i .e Input layer Neurons,Hidden layer Neurons,Output layer Neurons.
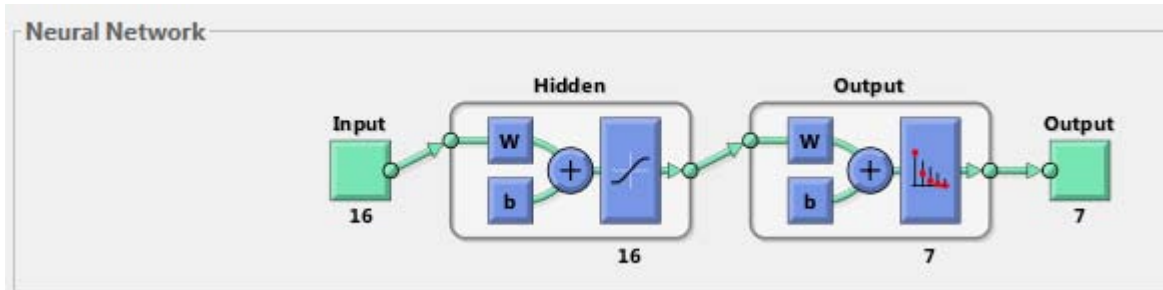
Figure 2: Three Layer Feed-forward MLP Classifier

Learning Phases in Neural Network

The artificial neural networks work mainly in three phases, which are

a)   Training Phase
b)   Validation Phase
c)   Testing Phase

The dataset is divided into training dataset, validation dataset and testing dataset. Training dataset is used for learning and to fit parameters of the classifier. To evaluate the success of the network, validation dataset is used to test the network's ability to generalize the data and tune the parameters of classifier. After fixed iterations have completely been carried out, the testing dataset is used in the trained network in order to estimate the error rate so that the network can recognize the pattern effectively. Figure shows the process of training, validation and testing phase in neural network.
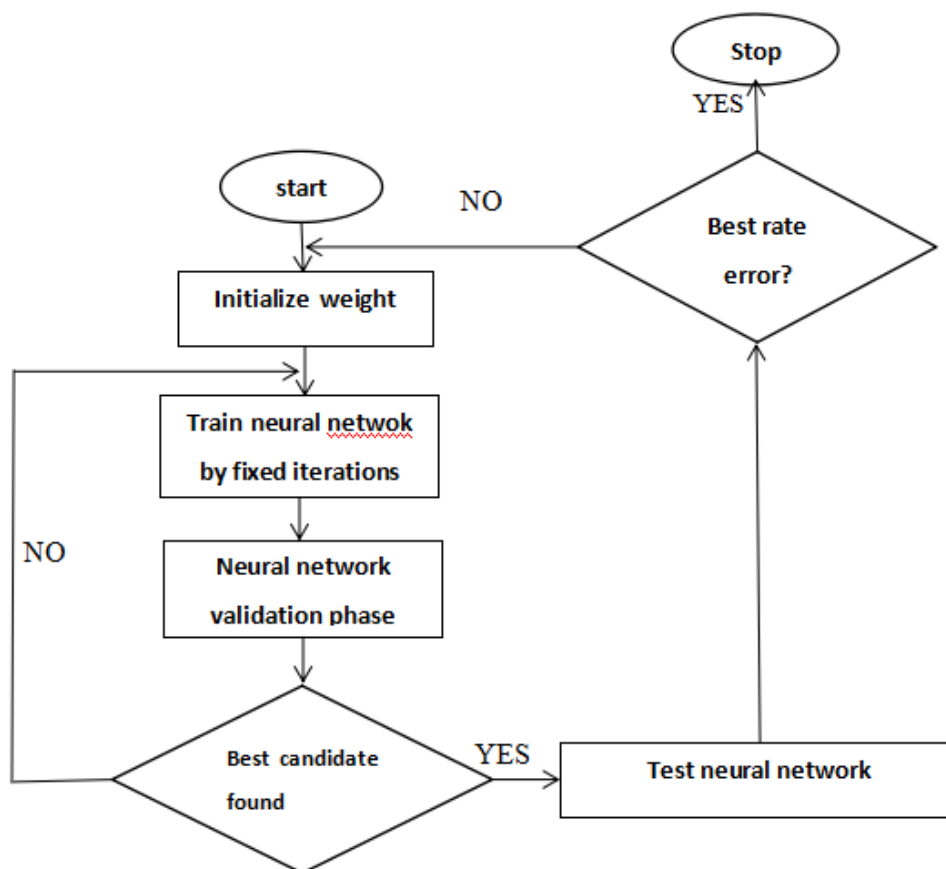

Figure 3: The process of training, validation and testing phase in neural network.

RESULTS

Performance Analysis

For this purpose comparison between target and network's output is done in testing set using various parameters to estimate the classifier performance. The parameters used for performance analysis are described below [18]

Biodiversity Classification Matrix

The performance of classifier is analyzed using confusion matrix [18].It displays the number of correct and incorrect predictions made by the model compared with the actual classifications in the test data. It is an *n*-by-*n* array showing relationships between true and predicted classes, where *n* is the number of classes[14].

In the field of artificial intelligence, a confusion matrix is a visualization tool typically used in supervised learning. Each column of the matrix represents the instances in a predicted class, while each row represents the instances in an actual class.

One benefit of this matrix is that it is easy to see if the system is confusing two classes (i.e. commonly mislabeling one as another).

A confusion matrix contains information about actual and predicted classifications done by a classification system. A confusion matrix can be made by using values of True Negatives, False Positives, False Negatives and True Positives. These are the standard terms for performance analysis of a classifier.

They represent the four different possible outcomes of a single prediction for a two-class case with classes "1" ("yes") and "0" ("no").

A false positive is when the outcome is incorrectly classified as "yes" (or "positive"), when it is in fact "no" (or "negative"). A false negative is when the outcome is incorrectly classified as negative when it is in fact positive. True positives and true negatives are obviously correct classifications.

Table Confusion matrix for two class classifier

Actual Class	Predicted Class	
	Yes	No
Yes	TP	FN
No	FP	TN

Classification Accuracy

The classification accuracy is the extent to which the classifier is able to correctly classify the exemplars and is summarized in the form of confusion matrix to the test data. This is defined as the ratio of the number of correctly classified patterns (TP and TN) to the total number of patterns (species) classified.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Sensitivity

The sensitivity of a classifier is the fraction of the Plant samples correctly classified as that specific species class. It is defined by equation below :

$$Se = \frac{TP}{TP + FN}$$

Specificity

The specificity is the fraction of normal species correctly classified as normal class. It is also called selectivity.

$$Sp = \frac{TN}{TN + FP}$$

Positive Predictive Value

It measures the ratio of correctly grouped positives.

$$PPV = \frac{TP}{TP + FP}$$

Negative Predictive Value

It calculates the proportion of negative cases that were correctly identified and defined by equation below

$$NPV = \frac{TN}{TN + FN}$$

False Positive Rate (FPR)

It is the fraction of all noneventsthat are not rejected. It is also known as Type I Error or α (alpha) or p-Value.

$$FPR = \frac{FP}{TN + FP}$$

Also   *FPR = 1 – Specificity*

False Negative Rate

It is also known as Type II Error or β (beta). This value is calculated as given in equation below

$$FNR = \frac{FN}{FN + TP}$$

Also,   *FPR = 1 – Sensitivity*

Overall Classification Accuracy

It is defined as the summation of diagonal elements in the confusion matrix divided by total number of classes. It is the fraction of the total number of leaf correctly classified.

Mean Square Error

Mean Squared Error is the average squared difference between outputs and targets. Lower values of (MSE) indicate better performance of the network and zero means no error.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(e_i)^2 = \frac{1}{N}\sum_{i=1}^{N}(t_i - a_i)^2$$

Where,   t - Target

a - Actual output

e - Error   N – Number of exemplars

Classification results for 7 stages of the PD

proposed work

Table.3 The table shows the sensitivity, specificity, and accuracy according its true positive,false negative, false positive values.

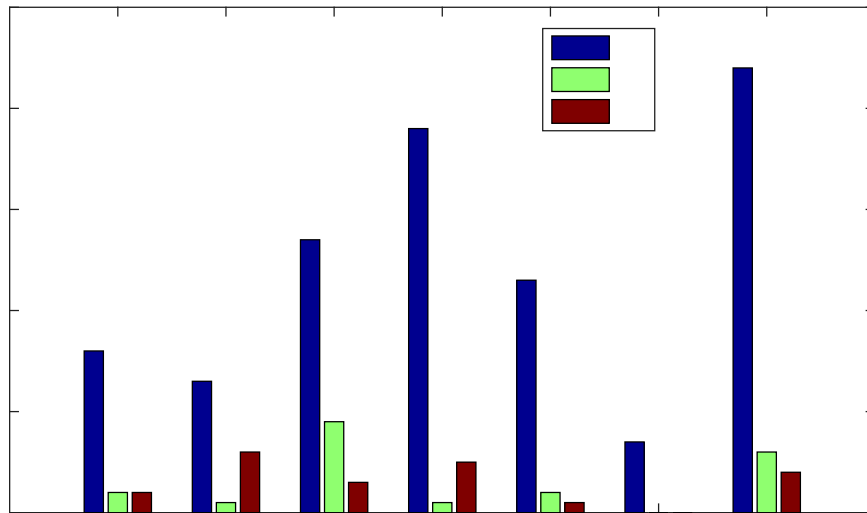| Parameters	TP	FN	FP	Sensitivity	Specificity	Accuracy
Stage 1	16	2	2	88.9	88.9	88.9
Stage 2	13	1	6	92.9	68.4	80.65
Stage 3	27	9	3	75.0	90.0	82.5
Stage 4	38	1	5	97.4	88.4	92.9
Stage 5	23	2	1	92.0	95.8	93.9
Stage 6	7	0	0	100	100	100
Stage 7	44	6	4	88.0	91.7	89.85

Figure.4. Graph for true positive,false nagative and false positive indexes.
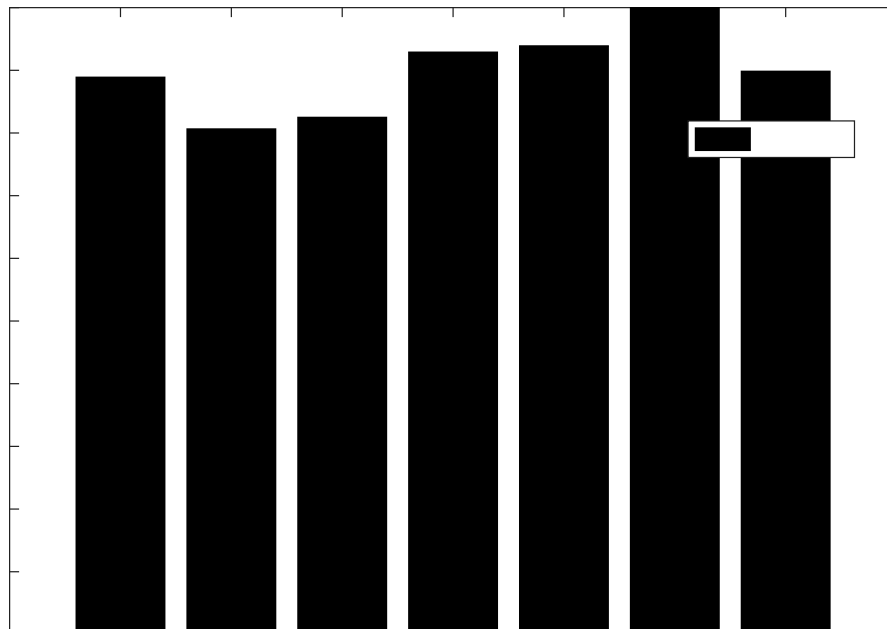

Figure.5.Performance eveluation using accuracy parameter.

These graph shows the performace of the system, according to its sensitivity, specificity, and accuracy parameters. These parameters are calculated from the confusion matrix.

4.CONCLUSION

Recently, diseases which related to neurodegenerative are increasing. Parkinson's disease (PD) is one of the most common neurodegenerative disease associated with the evolving growth of the elderly population. PD is a neurological disorder related to dopamine deficiency in part of brain called substantia nigra, with four main symptoms such as slow movement (bradykinesia), muscle stiffness (rigidity), shaking (tremor), balance or walking problem and voice impairment . Researchers have developed diagnostic

method for PD by using a number of pattern recognition methods. These are only able to classify subjects as either healthy or suffering from PD. Example acknowledgment technique for PD arrange characterization is imperative, since it help neurologist to give proper treatment and prescription to patients. For this we proposed ANN based stage classifier which classifies the test features into seven stages of the PD disease. The methodology of this study can be broken down into three stages: 1) the calculation of features; 2) the preprocessing and pre-selection of features; and (c) the application of a classification technique to all

possible subsets of features for the discrimination of healthy from disordered in seven stages. The information for this investigation comprise of 195 supported vowel phonations from 31 male and female subjects, of which 23 were determined to have PD. The time since diagnoses ranged from 0 to 28 years, and the ages of the subjects ranged from 46 to 85 years. Till now all existed work was on only two class classification i.e. healthy or unhealthy but stages were not considered. Therefore proposed method is implemented to classify data based on stages of the PD disease. Proposed method gives 88% accuracy in true classification of data in seven different stages of the disease.

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