European Journal of Molecular & Clinical Medicine
ISSN 2515-8260 Volume 08, Issue 03, 2021

A Performance Study of ML Models and Neural Networks for Detection of Parkinson Disease using Dysarthria Symptoms

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Abstract - Parkinson Disease (PD) is brain disorder that affects the central nervous system that results in damage of nerve cells causing dopamine to drop. PD has a severe effect on vocal features termed as Dysarthria symptoms including varied pitch, extended pauses, monotonous and speaking slowly or with a slur. In this paper, a dataset containing various vocal features are taken as input to analyze the performance of various Machine Learning algorithms including Naive Bayes, Random Forest Classifier, Support Vector Machines (SVM), Linear Regression, K Nearest Neighbor (KNN) and Neural Networks such as ANN and LSTM. The best classification accuracy was obtained by ANN around 90.00%.
Keywords - Parkinson Disease(PD), Dysarthria, Naive Bayes, Random Forest Classifier, Support Vector Machines(SVM), Linear Regression, K Nearest Neighbor(KNN), Artificial Neural Network(ANN), Long Short Term Memory(LSTM).

1. Introduction

An estimated 0.3% of the entire world's population and 1% of people above 60 years are diagnosed with PD [1]. Around 90% of patients with Parkinson disease (PD) experience various speech impairments during the course of their disease [2]. Affected patients develop dysarthria symptoms such as reduction in vocal intensity, disordered articulation with imprecise vowels, breathy weak voice and monotonicity [3]. Phonation is one of the severely damaged parts of speech production[4].

Various vocal tests have been devised such as sustained phonations and running speech texts for detecting PD[5].Therefore, In this work, we attempt to explore the performance of various machine learning based models and neural networks for an early detection of PD considering vocal features.

This following includes the recent studies on machine learning algorithms and neural networks used for detecting PD.

2. Related works

An AI classifier was built by Parisi et al. in [6] to detect PD. The dataset was taken from the UCI Machine Learning Repository and it consisted of 68 subjects with various vocal parameters scores. A Multi-Layer Perceptron accompanied by a cost function was customized to set feature scores.

Lagrangian Support Vector Machine (LSVM) for classification was provided with 20 features of high importance scores. The feature focused system achieved cent percentage accuracy.

Application of vocal features for remote monitoring of PD patients was proposed by Gabriel Solana Lavalle and et.al in [7]. The work focused on recent and large dataset publicly available.

Achraf Benba et al in [8], people with PD from the control subjects were separated. The 34 sustained vowels vocal data was collected from 34 people of whom 17 were PD subjects. 1 to 20 Mel-frequency cepstral coefficients (MFCC) were obtained for each patient. SVM with different kernel types was used for classification. Cross-validation technique was used by incorporating Leave One Subject Out (LOSO) The best accuracy was reported by linear kernel SVM taking in 12 MFCC coefficients.

The different features and speech signal processing algorithms were compared by C.O Sakar et al [9]. A new feature Tunable Q-factor wavelet transform (TQWT) was proposed in their work. The effectiveness of TQWT in extracting features for PD outperformed other speech signal processing. Different feature extraction and classifier combinations were used to analyze the effectiveness. Input Dataset was preprocessed using minimum redundancy- maximum relevance feature selection technique. RBF kernel SVM on all feature subsets reported highest accuracy 86%. Richa Mathur et al [10] suggested using weka tool for implementing the algorithms to perform preprocessing of data, classification and the result analysis method for predicting the PD. The method incorporated a k-NN along with Adaboost.M1, bagging, and MLP.

In [12], the study proposes a Deep Neural Network classifier containing a stacked auto encoder (SAE) and a softmax layer. Inherent information of the speech features was extracted using SAE while classification was done by the softmax layer. The results were analyzed considering two distinct datasets and were contrasted with other existing methods. Another PD diagnosis by Wroge et.al [13] depends on the efficiency of the DNN using physiological, behavioral and speech data collected with a mobile application. Two types of feature sets were extracted using Open Smile, an open source tool. At first, Minimum Redundancy Maximum Relevance (mRMR) and microarray data feature extraction algorithm. 60 features extracted using MFCC was taken as the next set of features. These feature sets loaded into a DNN and several ML classifiers. DNN gave a better accuracy than the other models. A thirteen layer Convolutional Neural Network was loaded with EEG Signals in [14]. The dataset included 20 PD diagnosed subjects and 20 healthy subjects. Performance metrics of the network gave accuracy of 88.25%, sensitivity 84.71% and specificity 91.77%. A smart pen was used in [15], by authors to capture handwritten patterns from healthy subjects and PD patients. Recent developments and research in wearables facilitate us in capturing disorders in motor skills. Pereira et.al [16] aimed to detect bradykinesia, described by difficulty in moving body parts. Data collected from wearable worn by PD diagnosed subjects and healthy subjects are loaded to different ML models and neural networks for feature vectors.

The structure of the paper is as follows: Section 2 presents the proposed methodology employed for PD detection. Section 3 entails the performance analysis of experimental results and discussion. The paper is concluded in Section 4.

3. Methodology

This section provides a synopsis of the proposed methodology and is shown in figure 1.

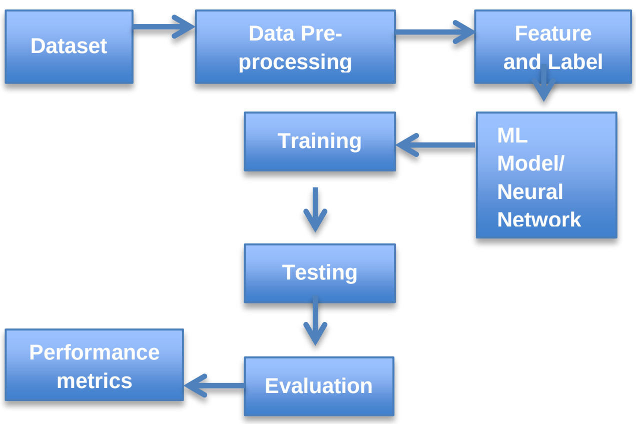

Figure 1: Proposed Framework

In this, the algorithms such as Naïve Bayes, Logistic Regression, Support Vector Machine, K-Nearest Neighbor, Random Forest, Artificial Neural Network and Long short term memory was analyzed. The initial step in the proposed work is the collection of data. Features are extracted using the data collected from the UCI, a machine learning repository which contains the voice data of both PD and healthy subjects [17]. The real time dataset was also added to it. The features are extracted using the fusion model of Mel frequency cepstral coefficient (MFCC) and Discrete wavelet transform (DWT). The dataset used for this work consists of 50 Parkinson and 50 normal patients. The proposed work takes in 26 features as shown in table 1 for detecting PD subjects. Features include Frequency Parameters, Amplitude Parameters, Harmonic Parameters and some Non Linear Parameters.

Table 1- Feature Extracts from Voice Signals

Features	**Group**
Jitter (Local) Jitter (Abs) Jitter (RAP) Jitter (PPQ5) Jitter (DDP)	Frequency Parameters

Shimmer (dB) Shimmer (APQ3) Shimmer (APQ5) Shimmer (APQ11) Shimmer (DDA)	Amplitude Parameters
Noise to Harmonic Ratio(NHR) Harmonic to Noise Ratio(HNR)	Harmonic Parameters
Pitch Periodic Entropy(PPE) Recurrence Period Density Entropy(RPDE) Detrended Fluctuation Analysis(DFA)	Non Linear Parameters

3.1 Machine Learning

Machine learning is a basic application of artificial intelligence (AI) providing systems the ability to automatically learn and improve from experience without being explicitly programmed. It focuses on the development of computer programs that can access the data and then use it learn for themselves

There are two types of techniques shown in figure 2 that machine learning uses: **Supervised learning** has the ability to train the model on known input and output data so that it is able to predict future outputs, and **unsupervised learning** has the ability to find hidden patterns or intrinsic structures in the input data

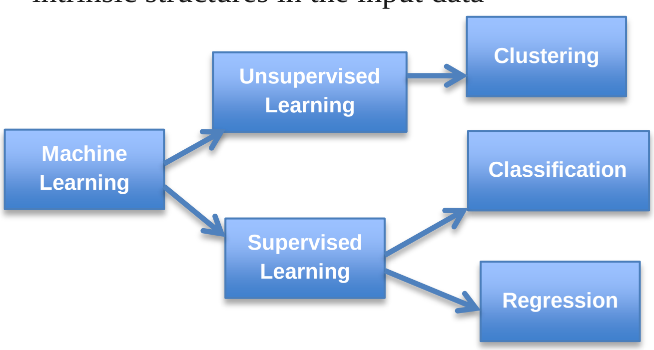

Figure 2: Supervised Learning

Supervised machine learning creates a model that makes predictions based on evidence in the presence of uncertainty. It takes a known set of input data and known responses to the data (output) and trains the model to generate a reasonable prediction for the response to new data. Supervised learning is based on classification and regression techniques to develop predictive models.

Classification techniques predict discrete responses. Classification models also classify input data into categories. Medical imaging, speech recognition, and credit scoring are included in these applications. Algorithms for performing classification includes support vector machine (SVM), boosted and bagged decision trees, *k*-nearest neighbor, Naïve Bayes, discriminant analysis, logistic regression, and neural networks.

Regression techniques predict continuous responses. Regression techniques can be used if one is working with a data range or if the nature of the response is a real number. Common regression algorithms include linear model, nonlinear model, regularization, stepwise regression, boosted and bagged decision trees, neural networks, and adaptive neuro-fuzzy learning.

3.2 Neural Network

Inspiration for neural network is human brain. It is a **Machine Learning** model to be more precise a deep learning model that is used in unsupervised **learning**. It is a web of interconnected entities known as nodes where each node is responsible for computations

a. **Long Short Term Memory (LSTM)**
Long short-term memory is an artificial recurrent neural network (RNN) architecture used in the field of deep learning. **RNN**'s special type is LSTM. The problem of long term dependency is overcome by LSTM. Generally the repeating modules of neural networked are linked to form a chain like structure for the RNN. A different repeating module with a chain like structure is seen in LSTM. Figure 3 shows the simple LSTM network.

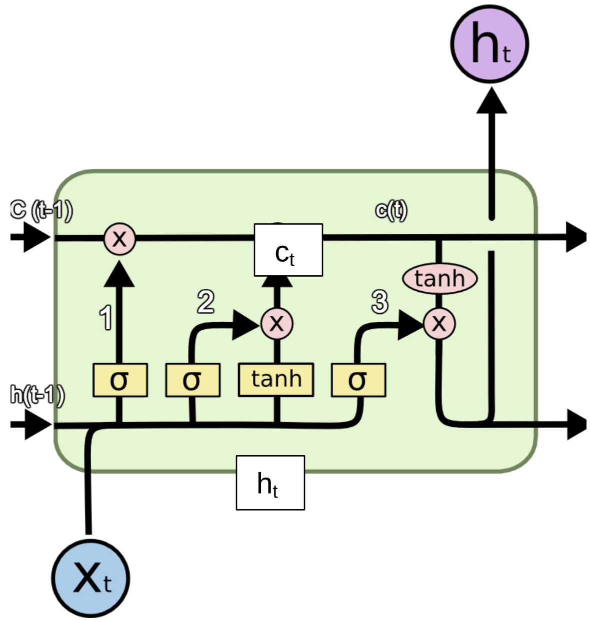

Figure 3: Four interacting layers of LSTM and its repeating modules

The cell state is the important thing of LSTM. The cell state runs through the entire chain and the information can be added/removed from the cell states by gates. It has 3 types of gates. The control gate controlled by f(t) that the controls the parts of long term state that has to be deleted . The input gate controlled by g(t) controls which part of g(t) to be added and the output gate controlled by o(t) controls which part of long term state should be read and output to be sent to y(t) and h(t). LSTM networks are mainly used to classify process and make predictions based on time series data, since there can be delays of unknown duration between important events in a time series working:

1. Define the Network
2. Compilation of Network
3. Fit the network
4. Evaluation of Network is then performed
5. Finally predictions are made according to the procedure

LSTM are much better than basic RNN unit since the training converges faster and detects long-term dependencies in that data.

b. **Artificial Neural Network (ANN)**

An artificial neuron network is a computational model which is based on the structure and functions of biological neural networks. Information that is flowing through the network affects the structure of the ANN because a neural network learns based on the input and output given

Framework of artificial neural networks (ANN):

- First random weights are assigned to all the linkages to start the algorithm
- Then using the inputs and the linkages activation rate is found for the hidden nodes
- Now using the activation rate of hidden nodes and linkages to output, activation rate for the output node is found
- error rate at the output node is then found and recalibration of all the linkages between hidden nodes and output nodes is done
- Now, using weights and error found at the output node, the error to hidden nodes is cascaded down
- Now recalibrate the weights between hidden and input nodes
- Repeat the process till the convergence criteria is met
- Finally using the linkage weight, score the activation rate of the output node.

4. Simulation Results and Discussions

In our work, to analyze the models and network implemented, performance metrics like Accuracy, Sensitivity, Specificity, F-1 Score and Matthew Correlation Coefficient (MCC) have been used. Various performance metrics are taken considering
Confusion Matrix that provides the True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN).

Accuracy is defined as the ratio of correctly predicted subjects who have PD to total number of subjects. Sensitivity is the proportion of patients with PD who test positive. Specificity is the proportion of patients without PD who test negative. F-1 Score relates the precision and sensitivity. Matthews Correlation Coefficient (MCC) considers TP, FP, FN and TN and gives the correlation coefficient between the PD diagnosed subjects and predicted PD subjects. It takes a value between -1 and +1. The formulae for the evaluation metrics are given below:

$$\text{Acuraccy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \tag{2}$$

$$\text{Specificity} = \frac{TN}{TN+FP} \tag{3}$$

$$\text{F1 Score} = \frac{2TP}{2TP+FP+FN} \tag{4}$$

$$\text{MCC} = \frac{(TP \times TN) - (FP \times FN)}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \quad (5)$$

Table2: Performance metrics for ML and Neural networks.

Model / Neural Network	Accuracy (%)	Sensitivity	Specificity	F-1 score (%)	MCC
NB	88.88	0.8	1.0	88.88	0.8
LR	77.77	0.75	0.8	75	0.55
SVM	77.77	0.75	0.8	75	0.55
KNN	59.15	0.5869	0.60	65.06	0.17
RFC	77.77	0.666	1.0	80	0.632
ANN	**92.00**	**0.8571**	**1.00**	**93.30**	**0.801**
LSTM	72.00	0.75	0.5	80	0.21

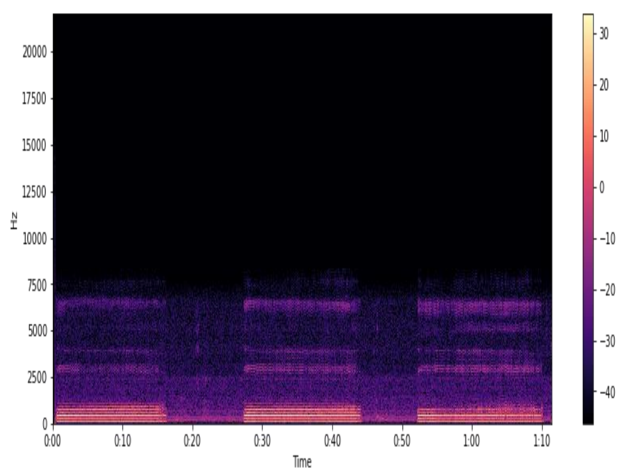

Fig 4: Spectrogram for normal person

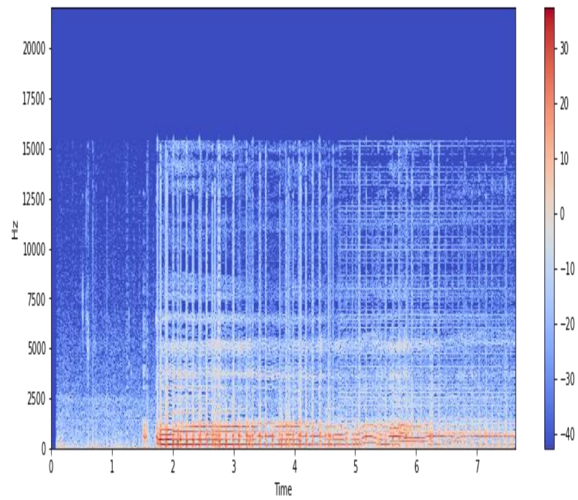

Fig 5: Spectrogram for Parkinson patient

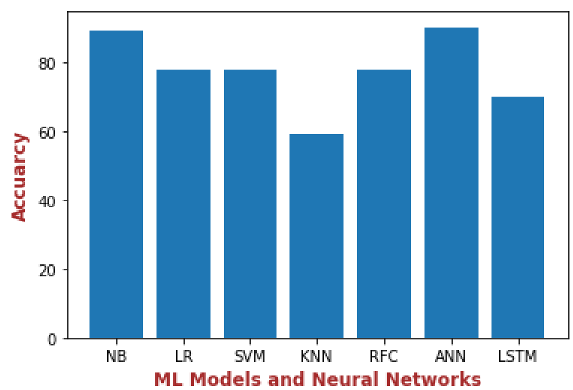

Fig 6: Graphical Representation of Accuracy for ML and Neural networks.

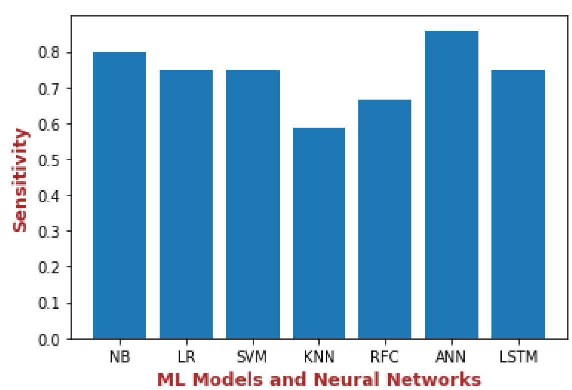

Fig 7: Graphical Representation of Sensitivity for ML and Neural networks.

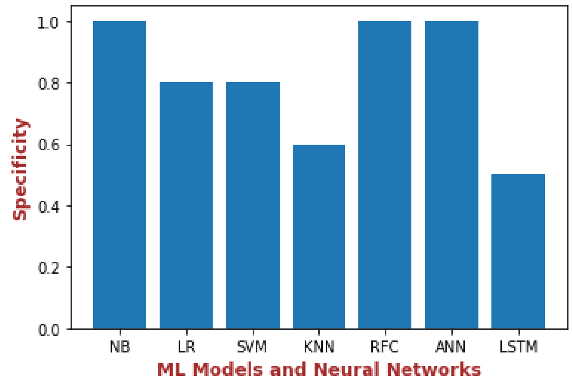

Fig 7: Graphical Representation of Specificity for ML and Neural networks.

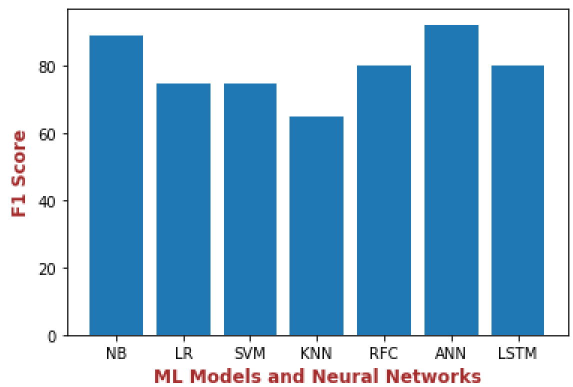

Fig 8: Graphical Representation of F1 Score for ML and Neural networks.

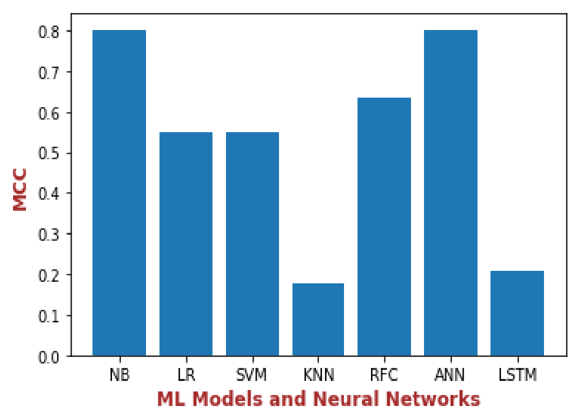

Fig 9: Graphical Representation of MCC Score for ML and Neural networks.

Another performance metric that provides classification performance is the ROC (Receiver Operating Characteristics) curve and AUC(Area under the curve). ROC is plot between the healthy patients detected with Parkinson (False Positive Rate) and PD patients detected with Parkinson (True Positive Rate).

The more the value of AUC, the better the model. Here we can see that ANN model has the highest AUC value of 0.92 followed by ML algorithm Naïve Bayes with 0.9. SVM and Linear Regression has the same performance with AUC value of 0.775. KNN has the least AUC value with 0.59.

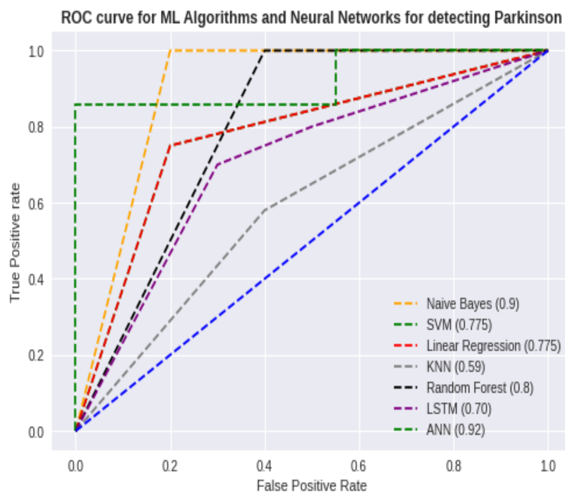

Fig 10: ROC for ML and Neural networks

5. Conclusion and future scope

The Artificial Neural Network performed well with 90% accuracy with an F1 score of 92.30% when compared to LSTM network. The performance of both the neural network can be improved if the dataset is huge. ANN shows a better sensitivity and specificity when compared to NB, LR, SVM and KNN. LSTM shows an accuracy of 701% which is better compared to KNN. In future the features can be extracted from different feature extraction techniques and can be tested with Transfer learning and Capsule networks.

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