Parkinsons Disease Classification using Deep Learning

[1]Qutaiba Humadi Mohammed, [2]Dr. E.Sreenivasa Reddy

Abstract--- *In the realm of neurological dysfunctional ailments, Parkinson's disease (PD) affects patients, mostly old. The patients suffer from this disease that affects their cognition, behaviour and mobility as well. In most cases, patients show symptoms like tremors, rigidity, bradykinesia, and flat facial expression. This disease has affected a lot of people around the world, causing severe pain and trauma to patients and their families. Globally, this dreaded disease has affected millions of people in various advanced as well as poorer countries causing large scale loss of productive life and health among men and women, especially the middle-aged and the elderly. Looking at the disease profile and its aggressive tendencies to progress, early stage detection offers the best possible treatment options and possibly positive outcomes, helping patients secure a good quality of life. The present paper proposes a Convolutional neural network -based methodology to predict the severity of disease in patients suffering from Parkinson's by analyzing Telemonitoring Voice Data Set of patients sourced from UCI. In order to predict disease severity among patients, 'Tensor Flow' deep learning library of* python *has been used for implementing our neural network. Significantly, our method produces better accuracy values than the accuracy values found in earlier research works.*

Key Words--- *Parkinsons, Diseases, symptoms, Telemonitoring.*

I. INTRODUCTION

In Parkinson's disease, a patient's brain and nerves get attacked by a slow paralytic condition in the core neurological system. Parkinson patients experience diminishing values of critical chemicals like dopamine stretching over a long time span, after which there occurs a complete absence of such chemicals in the nerve cells of an affected brain. Quintessentially, the prime function of Dopamine is that it carries messages from the brain as signals right across to the nerves. Once the cells that induce dopamine wear off, there occurs a breakdown in the transmission of messages, thereby resulting in stiffness in joints and partial or total cessation of muscular mobility after considerable thinning and weakening of the membranes. The worst part in such a context is that this debilitating degeneration affects almost all the muscles, including the ones that provide basic mobility function to various limbs. In such a critical condition, the patients suffer from debilitating slowness and difficulty in walking, speaking and swallowing, apart from kinetic difficulties in effecting animated facial and hand gestures and movements. In common cases, Parkinson patients suffer from speech disorders like loss of intensity that causes monotony in the pitch and volume, besides causing misplaced stress, intonation, besides

[12]ANU College of Engineering &Technology, Acharya Nagarjuna University, A.P-India.

Received: 22 Feb 2019 | Revised: 13Mar 2019 | Accepted: 05 Apr 2020

excessive pauses. Among a host of deficiencies, the prominent ones are quick and short rushes of speech, abrupt variations in rate, inchoate consonant sound, numbness in voice. As vocalic symptoms abound, their non-invasive properties make them easily recordable as voice data, thus being propped up as potential detection tools to be used in mobile devices. Data mining techniques have a lot of applications in medical research by combining advanced representational and computing techniques, bolstered by the prolific addition of the personal observations and ideas of expert medicos, resulting in creating tools for better treatment options. Computation identification of concealed patterns in datasets is done in Data mining, followed by development of predictive or classification models on the basis of earlier case studies that are in turn, used in hitherto unknown or emergent cases. As huge stockpiles of healthcare data can be traced in hospitals, medical centres, and research units, data mining techniques can enhance the quality of medical procedures and treatments by enabling medicos to devise effective interventional action plans. In fact, a host of classification techniques such as support vector machine (SVM), neural networks, decision tree, and Naïve Bayes offer the best possible options in such conditions. In view of the above factors, this study basically focuses on analyzing and comparing the available classification techniques, and then observes how these techniques are effective in making accurate diagnosis of the progression of Parkinson's disease. While studying the performance of the classifiers on real and discretized PD dataset, a comparative analysis of performances is done by applying the attribute selection algorithm.

Deep learning technique is preferred all over the world for its accurate analysis of unstructured data that include speech and audio signals. Typically, multiple layers of neurons populate contiguous stacks to create classification and feature selection models in Deep Neural Networks. In this work, the focus is to analyze patient's voice data by applying deep learning and classify into "severe" and "not severe" classes. In this work, UPDRS (Unified Parkinson's Disease Rating Scale) scores viz., total UPDRS and motor UPDRS scores are used as evaluation metrics. In the motor UPDRS, the motor ability of the patient is evaluated on a scale ranging between 0 & 108, while it is in 0-176 scale that total UPDRS scores are evaluated. Though a number of researchers have tried their hands at prediction of Parkinson's disease, yet not much has so far been reported to have accurately predicted disease progression and its severity, including the works applying many machine learning techniques. Earlier, Das et al. [1] have carried out a survey to identify available classification techniques engaged in diagnosis of Parkinson, which found neural network as offering more effective classifier functions in comparison with regression and decision tree. It may be noted that a majority of the earlier researchers have primarily tried to focus on feature extraction from speech signals for predicting the disease advancement in patients suffering from Parkinson's. In fact, voice recordings of patients were used to extract features for predicting the progression of the disease through application of Bagged decision trees in the study undertaken by Genain et al. [2], thereby clocking a 2% higher accuracy. Further, on the basis of UPDRS score, patients were classified into four classes Viz., Healthy, Early, Intermediate & Advanced by using Local Learning Based Feature Selection (LLBFS) from 9 best features selected out of the total 40-feature dataset in the study by Maleket al.[3] . Cole et al.[4] used wearable sensors to collect data and applied dynamic machine learning algorithms to identify the severity of tremors and Dyskinesia in Parkinson patients, whereas a sensor system was developed by Angeles et al.[5] for recording kinetic data from the arm for tracking fluctuations in severity while administering Deep Brain Simulation Therapy. Elsewhere, Adaptive Neuro fuzzy inference system (ANFIS) and Support Vector Regression(SVR) formed the basis of a new hybrid intelligent system developed by Nilashiet al.[8] to predict disease progression in Parkinson patients. In the work of Chen et al.[9], a PD diagnostic system was developed that sought to extract features through application of PCA, while classification was attained by using Fuzzy KNN. Disease progression in Parkinson patients was done through a combination of Fuzzy C-Means (FCM) clustering and KNN in the model proposed by Polat[10]. On the basis of parallel feed forward Neural Network, a prediction system for Parkinson disease was proposed by Åström and Koker[11]. In this case, final prognosis is determined after undertaking a comparative analysis between the resultant output and results of a rule-based system. Li et al.[12] suggested a nonlinear transformation method to introduce PCA for extraction of features by using fuzzy logic, while the frequency of Parkinson cases were predicted by applying SVM. Hariharan et al. [13] developed a hybrid intelligent system to attain precision in diagnosis through application of clustering, feature reduction and classification methods.

1.1. Voice Data

Typically, a message is verbally communicated by using a sound called as Voice while pronouncing a syllable, word or sentence. The sound waves carry the ideas and thoughts of a person through the air. Broadly, when a person speaks, the entire process passes through 4 different stages viz., Respiratory, Phonation, Resonation, Articulation. In the respiratory stage, breathing takes place through inhalation and exhalation. In the inhalation process, air is made to pass into the lungs by compressing the diaphragm, which is a muscle that separates the chest and abdomen. Conversely, air gushes out of the lungs in the exhalation process. While speaking, the expiratory air stream releasing from the lungs passes via the trachea or wind pipe to the larynx or the voice box and results in production of voice sound, which is then enlarged by resonators in the resonation stage. Then, the articulators' covert the tone produced in larynx to definite sound in articulation stage. Hence, it may be found that while producing voice, our speech organs make use of compression, vibration, amplification and modification [2]. However, when the voice is afflicted with disease like Parkinsons', then the patient manifests symptoms like slowness of speech, reduced loudness, low pitch, softer and inarticulate voice, lack of fluency, stuttering and stammering, vocal tremors etc. The patients' voice also exhibit negative manifestations like monotone in conversation, hoarse voice quality, besides inflexible and stiff laryngeal and ribcage muscle and hasty burst of speech. In essence, the Parkinsons' patients largely manifest symptoms like vocal fold tremors, breathiness, weakness and fluctuation of jaw, tongue and lip as indicative of the malaise and its progression.

II. Proposed Methodology

As exhibited in Fig. 1, the proposed work seeks to develop a methodology so that the onset, advancement and severity of the disease in a patient can be accurately predicted through application of deep learning techniques. In the initial stages, the generated voice data of the patients is analyzed, followed by the phase in which min-max normalization is applied to process the data. Then, a deep neural network is designed after the process is segregated into multiple layers, majorly designated as the input layer, hidden layers and output layer. The neurons populating the input layer are assumed as the selected attributes of the input data. However, the two neurons in output layer are labelled as “severe” or “non-severe” classes, which filter the normalized data via the designed deep neural network to perform training and testing in subsequent phases.

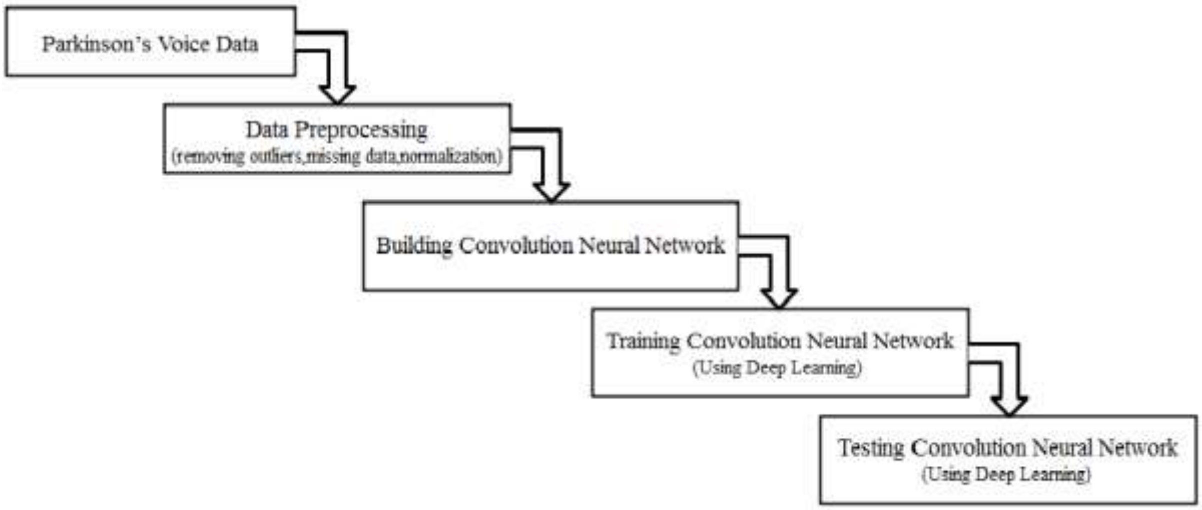

Fig.1. Proposed Framework Predicting Parkinson Disease

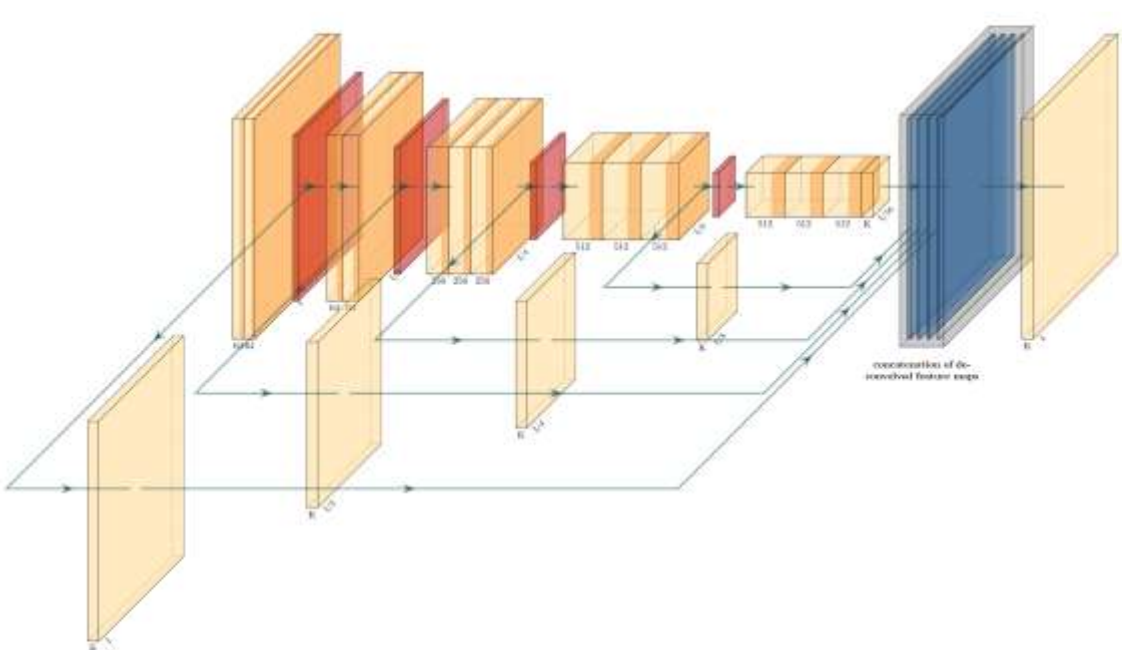

Fig.2. Convolution Neural Network Architecture

Fig.3. Implementation of Neural Network Architecture
Fig.3. Implementation of Neural Network Architecture

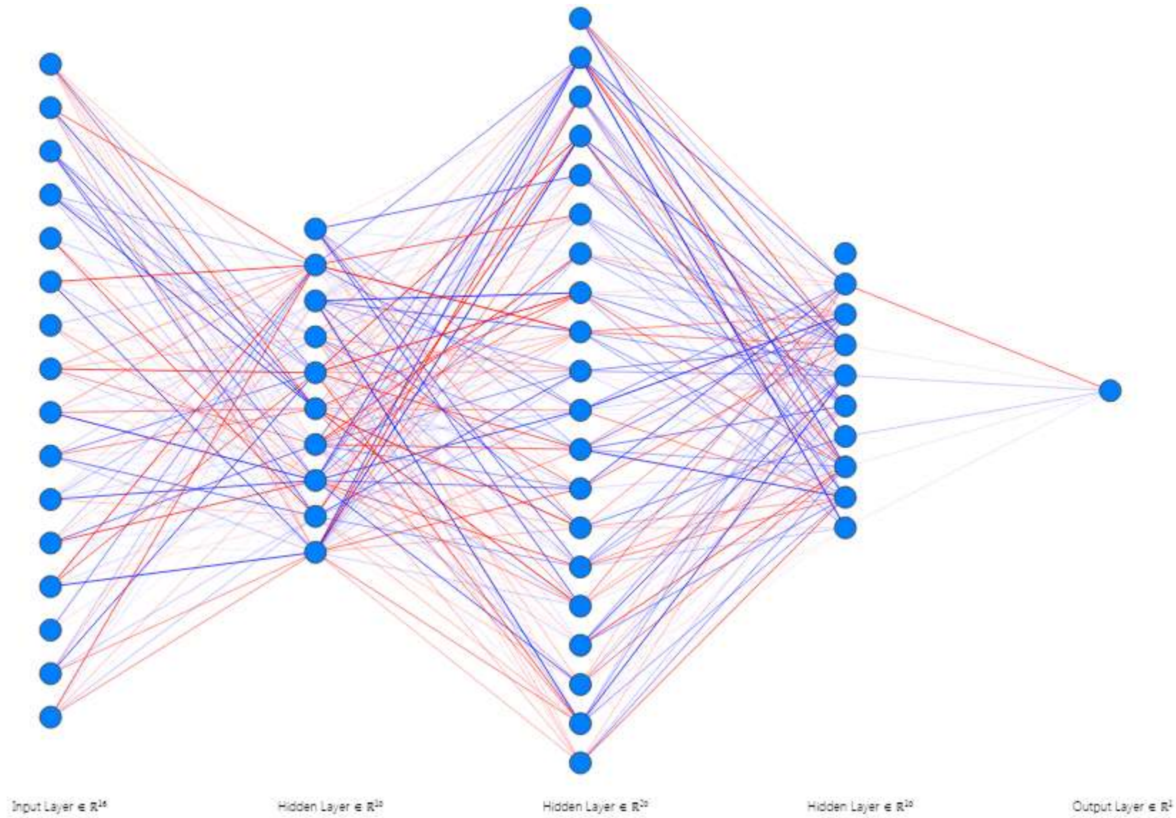

Fig.3. Implementation of Neural Network Architecture

III. Implementation

The implementation of the planned model has been done on a system comprising Intel Core i5-5200U CPU @2.20GHz and 8 GB RAM. A Deep Neural Network is implemented by using Python library, TensorFlow (tf.estimator) [14]. The dataset i.e. Parkinsons Telemonitoring Voice Data Set sourced from UCI Machine Learning Repository [15] contains biomedical voice dimensions belonging to a sample size of 42 patients. The data set has been prepared based on attributes like the number, age, and gender of the patient. The other significant attributes include time interval, Motor UPDRS and Total UPDRS, besides 16 biomedical voice attributes. The bulk of the dataset containing 5,875 voice recordings of select patients is stored in ASCII CSV format. Each patient contributes roughly 200 recordings (it can be identified through the first attribute i.e. subject number).

3.1. Data Pre-processing

By applying min-max normalization, the dataset has been normalized into a range of 0-1 in a column-wise manner by applying equation (1): (1) Where x= column value, min(x) = minimum value for that column and max(x) = maximum value for the same column.

3.2. Building the DNN

Multilayer perceptron (MLP): It refers to multilayer perceptron network (MLP) comprising several layers. Typically, a two-layer MLP network offers a complete and direct mutually connected feed neural network system comprising various layers like an input layer , a concealed layer as well as an output layer. The representative classification is exhibited in Figure 1. The output layer is counted, irrespective of being healthy or sick, while the input layer is not taken into account as its neurons have representation usage alone and do not count in the process. The neurons lining the input and hidden layers have individual connectivity with all other neurons found populating the proximate layer by virtue of weighted connections. Such neurons (see figure 2) add a threshold after calculating weighted sums of their inputs, wherein, the activity of neurons are calculated by the resultant sums through application of a sigmoid activation function.

In the data set, the total UPDRS score ranges between the least value of 5.0377 and an optimum value of 54.992, while the variation in motor UPDRS scores are found between the least score of 5.0377 and the optimum score of 39.511. Thereafter, the normalized data set is sliced into two parts, one containing 80 % for train, while 20% data set is assigned as test dataset. Furthermore, the engine UPDRS score and the total UPDRS score are fed by dedicated train and test data sets, designating such scores as the output variable in the matching files. The 16 biomedical voice data selected as features for classification have normalized values such as Jitter (%), Jitter (Abs), Jitter RAP, PPQ5, DDP, Shimmer (dB), Shimmer: APQ3, APQ5, Shimmer: APQ11, Shimmer DDA, NHR, HNR, RPDE , DFA and PPE. However, the output classes are labelled as "not severe" or "severe" in their classification. Table 1 exhibits the diverse metric ranges classified only as ‘severe’ or ‘non-severe’ classes in view of the presence of limited values in the data set. The algorithm creates an input pipe from the input data set, after which the iterators are defined as variables to scan the data set. In the designed algorithm, randomness is created by shuffling the data set. Once the input pipeline is defined, the input data is fed into the training model in the next step, which is executed by invoking the lambda function. In subsequent stages, after accumulating the data, training, evaluation and prediction functions are performed by the developed model. The hidden layer matrices are defined by assigning pre-initialized weights to the layer to execute the training function, after which the model is created and saved. The DNN classifier is fashioned through application of Tensor Flow with Keras as backend after which it is evaluated while the system is in process as well as in the end stage. In the designed neural network, we have arranged 16 units in the input layer, whereas the 3 hidden layers are assigned with 10, 20, 10 neurons in an orderly manner. Moreover, we assigned further training of 1000 and 2000 steps to the network.

IV. Experiments and Results

Experiment: 1 Univariate Analysis

The fig.4 shows box plot view of frequency variation of some variable like spread1 etc which have outliers.

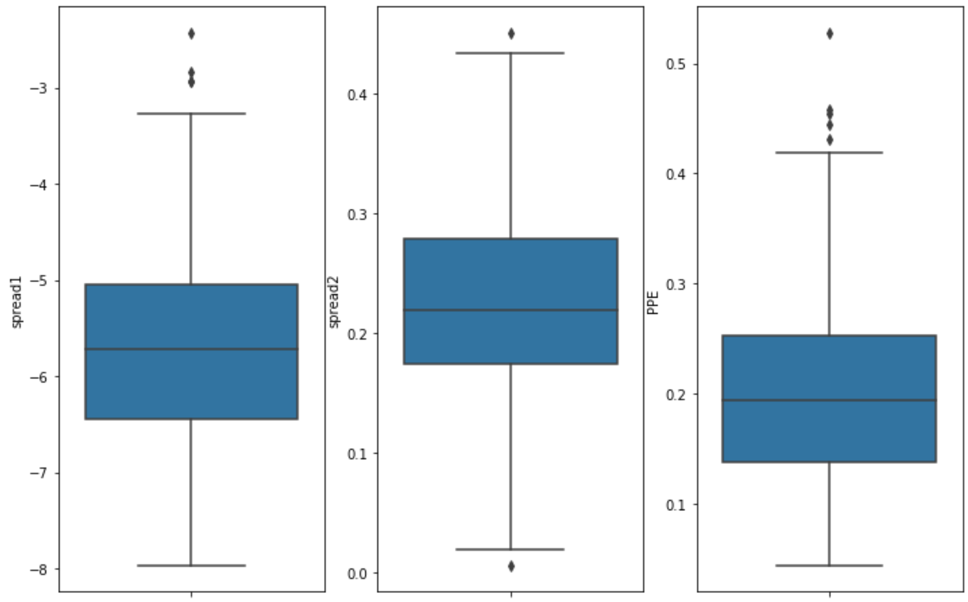

Fig.4.Box Plot of the 3 variable frequency variations (Spread1, Spread2, PPE)

In the next step important variable are extracted from the data set as shown in fig.5.

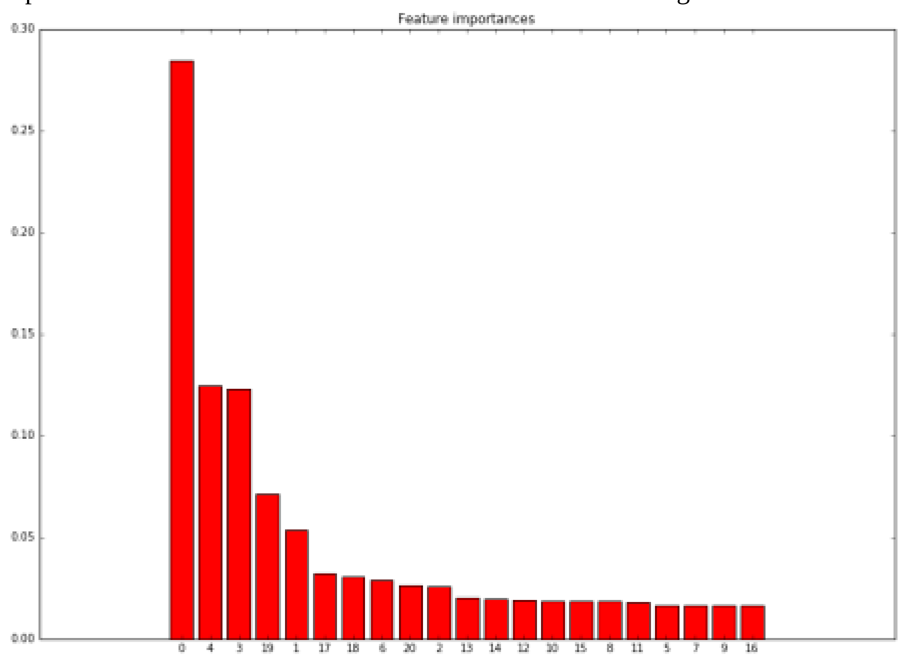

Fig.5. Variable of Importance

Based on the Z-score a threshold=3 as been taken to avoid the outlier in the given voice data set

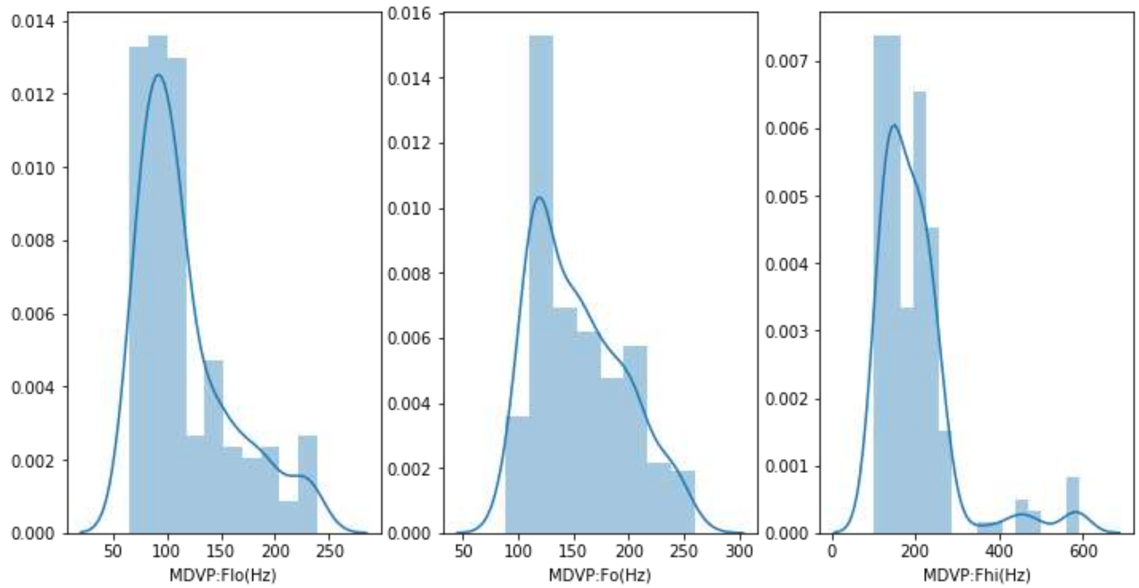

Fig.6.Vocal Fundamental Frequency (MDVP.Flo (Hz), MDVP.Fo (Hz), MDVP.Fhi (Hz))

The fig.6 shows measurement of vocal fundamental frequency. Positive Skewness is observed for low vocal frequency with the high values ranging between 75Hz and 125Hhz. The average vocal frequency is almost normally distributed with values lying between115Hz and 130Hz. It is observed that high vocal frequency didn't exhibits any skewness

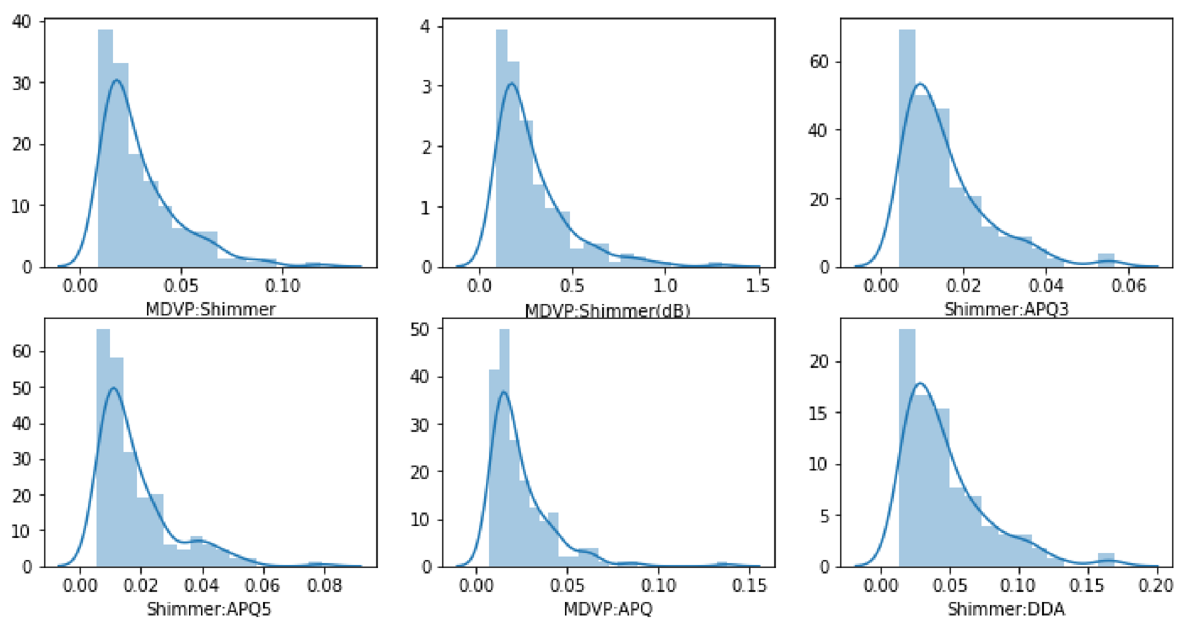

Fig.7.Measure of variation in amplitude

For all of the above graphs, we can observe that the measure of variation in amplitude is positively skewed

Received: 22 Feb 2019 | Revised: 13Mar 2019 | Accepted: 05 Apr 2020

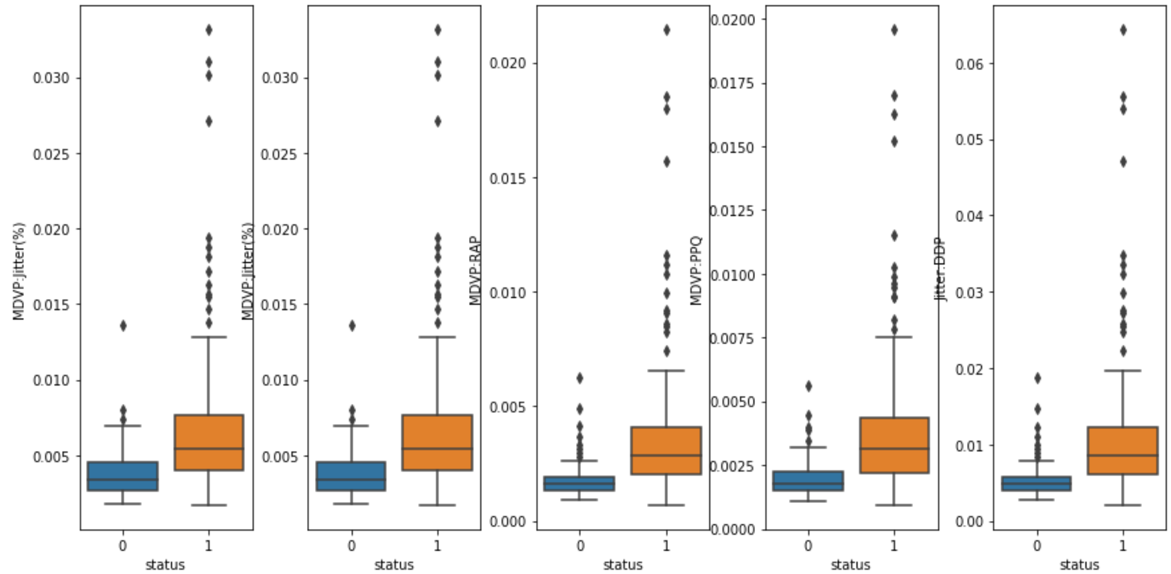

Fig.8. Values of Jitter

People who are suffering for PD tend to have higher values of jitter seems if the values goes above 0.15 we can confirm the patient is having PD. The variation of fundamental frequency is in a low range for people who are normal.

Experiment: 2 (PD Severity prediction on the basis of Total UPDRS Score)

In this context, an input dataset gets assigned 16 biomedical voice features with UPDRS score in its entirety is designated as output variable. The train registers a classification accuracy of 94.4422% in contrast to the test dataset attaining a precision of score of 62.7335%. After testing on UCI Parkinson's Telemonitoring Voice Data set, our results were compared with the results shown in evaluation model as discussed in the work by Nilashiet al.[8]. When compared to the previous cases wherein ANFIS and SVR were applied to predict disease progression among Parkinson patients, the levels reached in our work have better accuracy. Our achieved levels far outweigh the previously generated 47.2% average accuracy in total UPDRS score. In Fig.9, the classifier performance in terms of the comparative Total UPDRS scores is shown as given below:

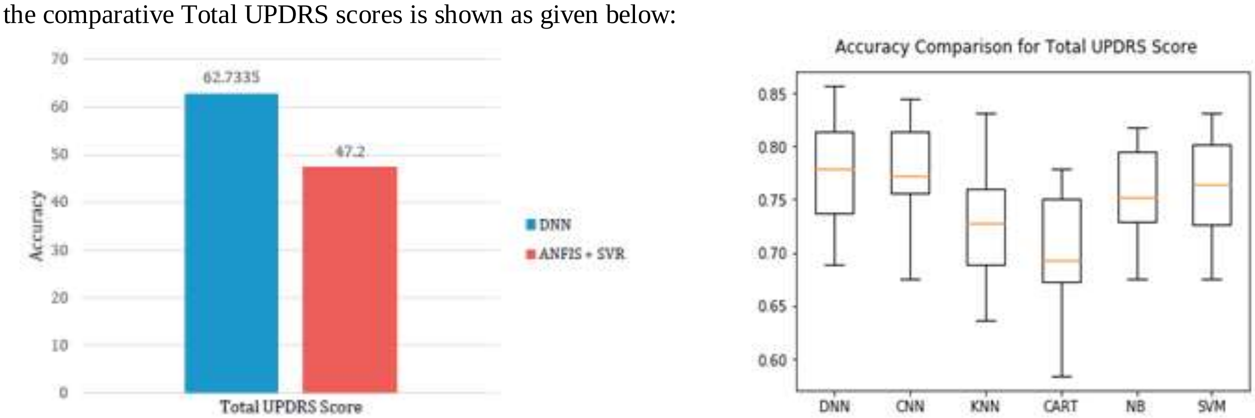

Fig. 9. Accuracy Comparison for Total UPDRS Score

Experiment 2(PD Severity prediction on the basis of Motor UPDRS Score)

In this context, an input dataset gets assigned 16 biomedical voice features with Motor UPDRS score in its entirety is designated as output variable. The train registers a classification accuracy of 83.367% in contrast to the test dataset attaining a precision of score of 81.6667%, leaving the average accuracy of 44.3% registered by Nilashiet al.[8] while various techniques were applied with regard to Motor UPDRS scores. . In Fig.9, the classifier performance in terms of the comparative Motor UPDRS scores is shown as given below:

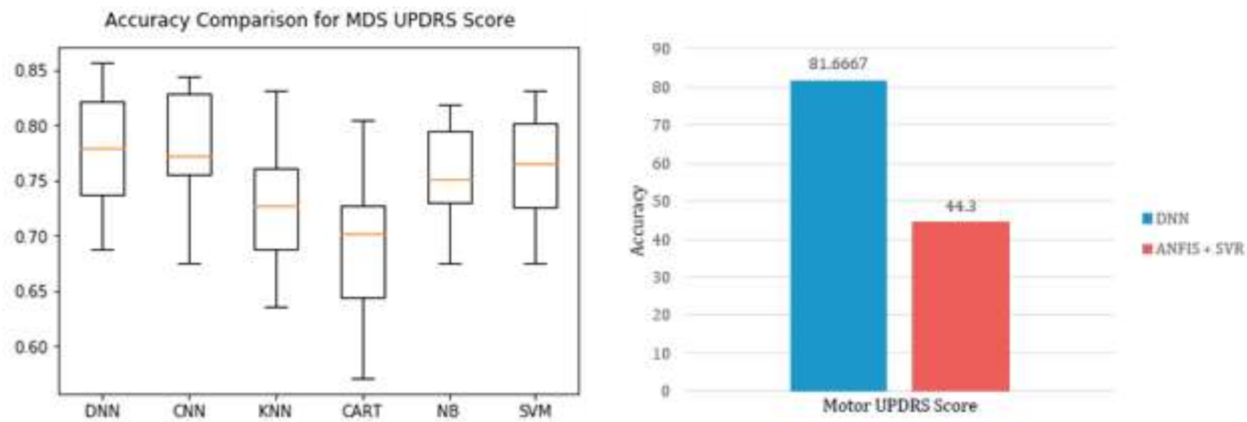

Fig. 10. Accuracy Comparison for Motor UPDRS Score

V. Conclusion

The present paper proposes a deep neural networks-based methodology for predicting progression of disease in patients suffering from Parkinson's by analyzing Telemonitoring Voice Data Set of patients sourced from UCI. In order to predict disease severity among patients, 'TensorFlow' deep learning library of python has been used for implementing our neural network. Significantly, our DNN model produced better accuracy values than the accuracy values found in earlier research works. In severity prediction, our motor UPDRS score-based classification performed superior as compared to classification done on total UPDRS score, conclusively proving itself as a better metric. Considering the dataset size of 5875 subjects, we have generated quite encouraging accuracy levels, which can further be enhanced by applying them on a larger dataset, with even more subjects, severity classes, larger voice dataset, apart from rest of the attributes that include gait and handwriting features.

REFERENCES

[1] Das R. (2010) "A comparison of multiple classification methods for diagnosis of Parkinson disease". Expert Systems With Applications"; 37:1568-1572.
[2] Genain N, Huberth M, Vidyashankar R. (2014) "Predicting Parkinson's Disease Severity from Patient Voice Features."
[3] Benmalek E, Elmhamdi J, Jilbab A. (2015) "UPDRS tracking using linear regression and neural network for Parkinson's disease prediction." International Journal Of Emerging Trends & Technology In Computer Science (IJETTCS); 4:189-193.
[4] Cole B, Roy S, De Luca C, Nawab S. (2014) "Dynamical Learning and Tracking of Tremor and Dyskinesia From Wearable Sensors." IEEE Transactions On Neural Systems And Rehabilitation Engineering; 22:982-991.
[5] Angeles P, Tai Y, Pavese N, Wilson S, Vaidyanathan R. (2017) "Automated Assessment of Symptom Severity Changes during Deep Brain Stimulation (DBS) Therapy for Parkinson's Disease." International Conference On Rehabilitation Robotics (ICORR).

[6] Galaz Z, Mzourek Z, Mekyska J, Smekal Z, Kiska T, Rektorova I et al. (2016) “Degree of Parkinson's Disease Severity Estimation Based on Speech Signal Processing.” 39th International Conference On Telecommunications And Signal Processing (TSP).
[7] Asgari M, Shafran I. (2010) “Extracting Cues from Speech for Predicting Severity of Parkinson's Disease.” IEEE International Workshop On Machine Learning For Signal Processing. 81.6667 44.3 0 10 20 30 40 50 60 70 80 90 Accuracy Motor UPDRS Score DNN ANFIS + SVR
[8] Nilashi M, Ibrahim O, Ahani A. (2016) “Accuracy Improvement for Predicting Parkinson’s Disease Progression”. Scientific Reports; 6. 34181
[9] Chen H, Huang C, Yu X, Xu X, Sun X, Wang G et al. (2013) “An efficient diagnosis system for detection of Parkinson’s disease using fuzzy k-nearest neighbor approach.” Expert Systems With Applications; 40:263-271.
[10] Polat K. (2012) “Classification of Parkinson's disease using feature weighting method on the basis of fuzzy C-means clustering.” International Journal Of Systems Science; 43:597-609.
[11] Åström F, Koker R. (2011) “A parallel neural network approach to prediction of Parkinson’s Disease.” Expert Systems With Applications; 38:12470-12474.
[12] Li D, Liu C, Hu S. (2011) “A fuzzy-based data transformation for feature extraction to increase classification performance with small medical data sets.” Artificial Intelligence In Medicine; 52:45-52.
[13] Hariharan M, Polat K, Sindhu R. (2014) “A new hybrid intelligent system for accurate detection of Parkinson's disease.” Computer Methods And Programs In Biomedicine; 113:904-913.
[14] Getting Started with TensorFlow. https://www.tensorflow.org/versions/r1.1/get_started/get_started
[15] Tsanas A, Little M, McSharry P, Ramig L. (2010) “Accurate Telemonitoring of Parkinson's Disease Progression by Noninvasive Speech Tests.” IEEE Transactions On Biomedical Engineering; 57:884-893