

# Early Detection of Parkinson Disease using Voice Data

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**Abstract**—Parkinson’s disease affects over 10 million people worldwide, with approximately 20 percent of patients not being diagnosed. Clinical diagnosis is expensive because there are no specific tests or bio-markers, and it can take days to diagnose because it is based on a comprehensive evaluation of the individual’s symptoms. Existing research either predicts a Unified Parkinson Disease Rating Scale rating, uses other key Parkinsonian features to diagnose an individual, such as tapping, gait, and tremor, or focuses on different audio features. In this paper, we are focusing on using the voice aspect for the early detection of the disease. We use the University of California Irvine (UCI) Parkinson data set. This data set contains various parameters regarding voice jitter. The data set first undergoes preprocessing. We have used a Feedforward Neural Network (FNN) model to acquire early on detection using the above data set. Our model has achieved an efficiency of 97.43 percent. This efficiency can be improved by using even a larger and diverse data set.

**Keywords**- Feedforward Neural Network (FNN); Parkinson Disease; Machine Learning.

## I. INTRODUCTION

Parkinson’s disease is a progressive disorder that affects the nervous system and the parts of the body controlled by the nerves. Symptoms start slowly. The first symptom may be barely noticeable. Although Parkinson’s disease can’t be cured, medications might significantly improve your symptoms. Getting this treatment in early stages can be very helpful in dealing and controlling the symptoms.

Parkinson’s signs and symptoms may include:

- Tremor: A tremor, or rhythmic shaking, usually begins in a limb, often your hand or fingers. You may rub your thumb and forefinger back and forth. This is known as a pill-rolling tremor.

- Rigid muscles: Muscle stiffness may occur in any part of your body. The stiff muscles can be painful and limit your range of motion. Impaired posture and balance. Your posture may become stooped. Or you may fall or have balance problems as a result of Parkinson’s disease.

- Speech changes: You may speak softly, quickly, slur or hesitate before talking. Your speech may be more of a monotone rather than have the usual speech patterns.

- Writing changes: It may become hard to write, and your writing may appear small.

All these symptoms can be recorded using different types of sensors. But, one of the most common early signs for Parkinson’s disease is the change in voice quality. Thus, we have chosen to go with voice data as our main data set. The Wireless sensors will collect the data and send it to the Model to be processed and analyzed, which can then help the user/patient by giving it insights into possible problems. The data can also be used to do an early diagnosis of the disease.

Early detection for PD (Parkinson’s Disease) can help as treatments such as levodopa/carbidopa are more effective when administered early on in the disease. Non-pharmacologic treatments, such as increased exercise, are also easier to perform in the early stages of PD and may help slow down disease progression. But, the problem is PD is very difficult to diagnose in the early stages. Parkinson diagnosis can take months and even years, by which the patient may be beyond help. So even if the prediction doesn’t definitively define if the patient has PD, it can help warn the person of a very strong possibility. Thus, certain parameters can be checked to determine this. One of the most early signs for PD that occurs in about 75 percent to 90 percent patients are changes in voice. Thus, we have proposed a prediction model that uses voice parameters to predict almost accurately if the person may or may not have PD.

## II. LITERATURE REVIEW

The authors use a semi-supervised competitive learning algorithm (SSCL) to classify the voices of Parkinson's patients as either dysphonic or non-dysphonic. The SSCL algorithm is trained on a dataset of both labeled and unlabelled voice samples to improve its accuracy in classifying dysphonic voices [1].

They have collected voice samples from 58 Parkinson's patients and 31 healthy controls, and used various acoustic features, such as jitter and shimmer, to train and test the SSCL algorithm. They found that the SSCL algorithm had an accuracy of 89.7% in classifying dysphonic voices, which outperformed other machine learning algorithms such as support vector machine (SVM) and random forest (RF).

The study also showed that the acoustic features used by the SSCL algorithm were significantly different between dysphonic and non-dysphonic voices, and that these features were related to the severity of Parkinson's disease [1].

The authors conducted experiments to compare the performance of SVM and NN for image classification. They may have used standard datasets for evaluation and discussed the results in terms of accuracy, precision, recall, and other relevant metrics. The Neural network model performed better than the SVM by a small margin. It can be noted that Neural Network can perform better for even larger data sets, giving it an upper hand over SVM [2].

The authors explain that neural networks are inspired by the structure and function of the human brain and consist of multiple interconnected nodes or neurons. They describe the three main types of neural networks: feedforward neural networks, recurrent neural networks, and convolutional neural networks.

They also explain the training process for neural networks, which involves adjusting the weights of the connections between neurons to minimise the error between the predicted and actual outputs. They describe various training algorithms, such as back-propagation and stochastic gradient descent, which can be used to optimise the weights. The advantages and disadvantages of using neural networks were also discussed. On the one hand, neural networks are capable of modelling complex non-linear relationships between input and output variables, making them useful for tasks such as image and speech recognition. On the other hand, neural networks can be computationally expensive to train and require large amounts of data to avoid overfitting. Thus we have gone with FNN (Feedforward neural network) that is more efficient than other

classifiers, and has potential to retain that efficiency in real-time huge data [3].

They also discuss about the importance of feature selection, proper evaluation of machine learning models, and combining techniques to improve the performance of individual classifiers. They discuss various combining techniques, such as bagging, boosting, and stacking, that can be used to improve the accuracy of machine learning models, including neural networks [3].

The authors used data from the Parkinson's Progression Markers Initiative (PPMI) database, which contains clinical and demographic information of PD patients and healthy controls. They applied feature selection techniques to identify the most important features that could be used to predict PD. They then trained and tested several machine learning models, including logistic regression, random forest, support vector machine (SVM), and extreme gradient boosting (XGBoost), to predict PD using these features.

The results showed that the XGBoost algorithm outperformed the other models in terms of accuracy, sensitivity, specificity, and area under the receiver operating characteristic (ROC) curve. The authors also found that age, gender, education level, and some clinical features such as the Movement Disorder Society-Unified Parkinson's Disease Rating Scale (MDS-UPDRS) and Montreal Cognitive Assessment (MoCA) scores were important predictors of PD.

The study provides insights into the use of machine learning algorithms for the early detection of PD, which could improve patient outcomes by enabling early interventions and treatments. The findings also highlight the importance of feature selection and the use of appropriate machine learning algorithms for predictive modelling [4].

Aimed to develop a novel approach to detect Parkinson's disease (PD) by analyzing voice patterns. The authors collected voice samples from two groups of participants: individuals diagnosed with PD (PD group) and healthy individuals (control group). They extracted a total of 19 acoustic features from the voice samples, including fundamental frequency, jitter, shimmer, and others. The authors then ranked the importance of these features using a statistical technique called the Wilcoxon rank-sum test. Based on the ranked features, the authors developed an optimized support vector machine (SVM) classifier to distinguish between the two groups.

In this study, The authors recognised the significance of speech analysis as a non-invasive method for diagnosing and monitoring Parkinson's disease. They aimed to create a comprehensive dataset that encompasses various speech tasks and characteristics to aid in research related to the disease.

The dataset includes sustained phonations, monologue speeches, reading tasks, and potentially other types of sound recordings. These recordings were then subjected to detailed analysis to extract various speech features. The authors emphasise the potential benefits of using a multi-modal dataset, as it allows for a more nuanced understanding of the impact of Parkinson's disease on different aspects of speech. Thus, we decided to choose voice data, as it is a non-invasive and can provide insights about speech impairment due to the disease [5].

The performance of the classifier was evaluated using two metrics: accuracy and area under the receiver operating characteristic curve (AUC). The results of the study showed that the SVM classifier based on the ranked voice features achieved an accuracy of 94.23% and an AUC of 0.99. These results suggest that voice patterns can be used as a reliable biomarker for the detection of PD.

The study highlights the potential of using voice patterns as a non-invasive and cost-effective tool for early detection of PD. The authors suggest that their approach can be further developed and integrated into mobile applications or home-based monitoring systems to facilitate early diagnosis and improve the management of PD. Even our current data set has similar features and that means that even our model is susceptible to the same development and integration into mobile applications[6].

In this study, authors have designed an empirical model with six classification algorithms. The dataset consists of MDVP voice features. The classification models were used to generate new features and classifications from the original data. Models used are Decision tree, Random forest, Neural Network, Deep Learning, Gradient Boost tree, SVM. The empirical model shows an accuracy of 87.18% which is primarily due to Random forest algorithm not requiring hand-crafted feature extraction. Pointing out the fact, there is a need for automatic feature extraction, that cannot be done by human logic. Hence, requiring the likes of a Neural network [7].

In this paper, the authors highlight the importance of early detection and assessment of voice disorders in PD, as these disorders can significantly impact a patient's quality of life. They note that traditional speech and language assessments may not be sufficient in identifying specific voice disorders associated with PD, and thus specialised assessments are needed.

They also discuss the use of technology in assessing voice disorders in PD, including telemedicine and smartphone applications. They suggest that these technologies can provide convenient and cost-effective ways to assess voice disorders in

PD, especially for individuals who live in remote areas or have limited access to healthcare services[8].

### III. PARKINSON EARLY DETECTION USING VOICE FEEDFORWARD NEURAL NETWORK MODEL

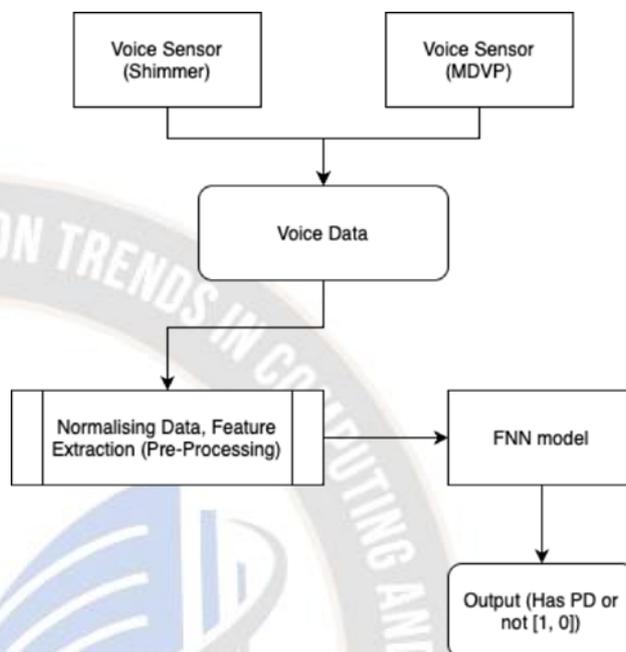


Fig 1. Proposed work flow diagram

The proposed model uses data acquired from using Wireless Sensors that will be attached on the suspected patient's body, namely Shimmer3 and Multidimensional Voice Program (MDVP) sensors, to capture voice related data. In our case we have used a UCI Database that has aggregated the data from the same. This data is further processed pre-processed and fed to the FNN model, which will predict if the patient has a valid possibility of being infected by Parkinson Disease or not. To monitor/compare the following FNN model's proficiency, we also fed this data as input to other general Classification models.

The Fig 1 flowchart explains how the our model works, from data acquisition to preprocessing, and predicting the output

#### A. Data set

This data set is composed of a range of biomedical voice measurements from 31 people, 23 with Parkinson's disease (PD). It consists of a total of 197 instances and 23 parameters.

The UCI Database has the following noticeable parameters :

- MDVP : Multidimensional Voice Program has several parameters that can assess voice quality, like Jitter, which is the cycle-to-cycle variability of the period

duration of the acoustic signal coming from voice production, RAP, which is five measures of variation in fundamental frequency, and more.

- Shimmer : Shimmer and Jitter both are acoustic characteristics of voice signals, caused by irregular vocal fold vibration. They are perceived as roughness, breathiness, or hoarseness in a speaker's voice. It also has various sub-parameters related to it.
- Status : Which tells if a patient has Parkinson's (1) or not (0)
- Other : Other parameters such as NHR, which assesses voice quality, HNR, which is a measure that quantifies the additive noise in voice signal, and more are present.

<https://data.world/uci/parkinsons-telemonitoring>

### B. Pre-processing data

Consists of Feature extraction, Skewness reduction and Scaling

Feature Extraction: To extract only correlating features, we find correlation between 'Status' and all the other features using corr() function in the pandas library. It uses Pearson's coefficient. Formula for Pearson's coefficient calculation :

$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n \sum x^2 - (\sum x)^2][n \sum y^2 - (\sum y)^2]}}$$

Where,

- r = Pearson coefficient
- n= number of pairs
- $\sum xy$  = sum of products of the paired x and y values
- $\sum x$  = sum of the values of the x-variable in a sample
- $\sum y$  = sum of the values of the y-variable in a sample
- $\sum x^2$  = sum of the square of values of the x-variable in a sample
- $\sum y^2$  = sum of the square of values of the y-variable in a sample

For any features having negative correlation coefficient we convert them in to positively correlating features by modifying

them so :

$$x' = \frac{1}{x}$$

Where,

- x' = inverted values
- x = values of the x-variable in a sample

Then we filter out any features having correlation coefficient less than 0.2, and obviously remove 'Status' itself too. This leaves us with moderately positively correlating features.

Now, the data is split into features, consisting of filtered features values and labels, consisting of the 'Status'.

Scaling : We perform min max scaling as it facilitates modeling, and reduces the impact of different scales on the accuracy of machine learning models. Thus simple column wise scaling takes place.

Formula for Min Max Scaling:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)}$$

Where,

- x' = scaled values
- x = values of the x-variable in a sample

This scaling takes place on only features, which are further split into train and test sets alongside 'Status' forming xtrain, xtest, ytrain, ytest respectively.

Input : xtrain, xtest, ytrain, ytest

Output : Predicted output

1: Start

2: `FNNModel = Sequential(Dense(units=8000, activation='relu'), Dropout(0.4), Dense(units=4000, activation='relu'), Dropout(0.4), Dense(units=500, activation='relu'), Dropout(0.4), Dense(units=1, activation='sigmoid'))`

3: `Opt = OptimizerAdam(learning_rate=0.001)`

4: `FNNModel.compile(loss='binary_crossentropy', optimizer= Opt, metrics = 'accuracy')`

5: `FNNModel.fit(xtrain, xtest, batch_size=6, epochs=12)`

6: `FNNModelScore = FNNModel.evaluate(xtest, ytest)`

7: `FNNModelOutput = FNNModel.predict(xtest)`

8: *If any value above 0.25 then 1 else 0 for all values in FNNModelOuput*

9: `Predicted Output = FNNModelOutput.flatten()`

11: Stop

#### IV. RESULTS AND DISCUSSION

This confusion matrix explains to the user how and what the model predicted. So, the matrix shows that there are truly 4 people that are healthy, and 3 people might have Parkinson's, but those 3 people are actually healthy. And 32 people are predicted to have PD and actually have PD.

	Predicted Healthy	Predicted Parkinson's
True Healthy	4	3
True Parkinson's	0	32

Fig 3. Confusion matrix for Test and Predicted Healthy and Infected

This shows that the model does not fail to predict if a person will have PD but might misjudge some healthy people as infected. To sum up, as this is a sort of warning system for the early detection, the people who are shown to be infected can further get check ups and other procedures done.

The below graphs show the interpretation of the test and predicted healthy and infected patients, gives a better view as to how the model performs.

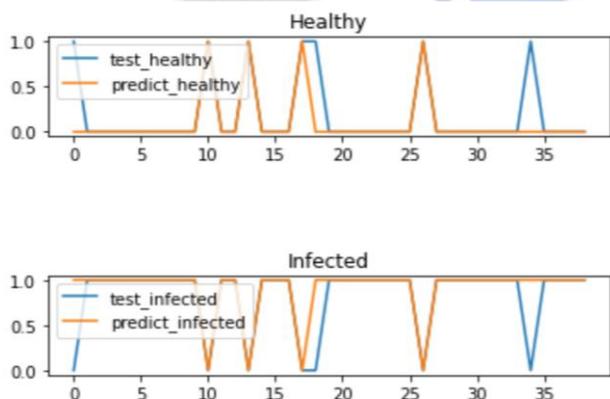


Fig.4 Shows Individual plotting of Test and Predicted, Healthy and Infected, respectively

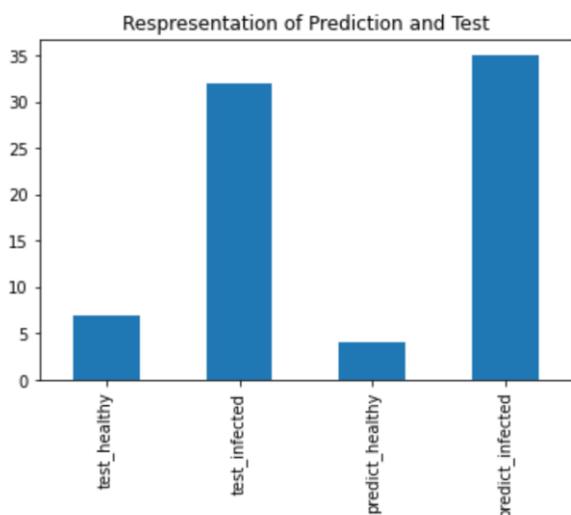


Fig.4 Bar Graph of all the Healthy and Infected Patients

The performance of our FNN model has been compared with some of the good ML classifiers on the same data set. The other two classifiers namely XGBClassifier and Support Vector Classifier (SVC) gave 97.43 percent and 87.89 percent accuracy respectively.

While ours recorded 97.43 percent. Our FNN model performed way better than we expected considering the size of the data set. Neural networks generally require continuous larger data sets to achieve maximum proficiency, and thus we expect our model to perform better than XGBClassifier over a larger data set or while in real-time application use which provides continuous data.

One of the reasons for achieving the high efficiency is due to the preprocessing data stage, where we performed feature extraction and modification, coupled with normalization, and scaling of data.

#### V. CONCLUSION

Parkinson Disease (PD) detection, especially in the early stages is very important and extremely helpful. We can enable this detection using technology, by the help of Deep learning, that is finely tuned neural networks.

In our proposal, we are using a data set that has captured voice data from Shim-mer3 and MDVP sensors. We then clean and adjust and then process that data using our FNN model designed to predict if the patient may or may not have PD, which it does with a significantly high efficiency (92.3 percent).

Future work on this current project can include, expansion of data set and increasing the type of data being processed from just vocal to motor skills and many other aspects. It can also include more enhancements in the same model to make it more accurate. Also, deployment of this particular in real time applications.

#### REFERENCES

- [1] Bao G, Lin M, Sang X, Hou Y, Liu Y, Wu Y. Classification of Dysphonic Voices in Parkinson's Disease with Semi-Supervised Competitive Learning Algorithm. Biosensors. 2022 Jul 9
- [2] Chaganti, Sai Yeshwanth, et al. "Image Classification using SVM and CNN." 2020 International Conference on Computer Science, Engineering and Applications (ICCSEA). IEEE, 2020.
- [3] Kotsiantis, Sotiris B., Ioannis D. Zaharakis, and Panayiotis E. Pintelas. "Machine learning: a review of classification and combining techniques." Artificial Intelligence Review 26.3 (2006): 159-190.
- [4] Kumari, LV Rajani, et al. "Detection of Parkinson's Disease using Extreme Gradient Boosting." 2021 5th International Conference on Trends in Electronics and Informatics (ICOEI). IEEE, 2021.
- [5] Sakar, Betul Erdogan, et al. "Collection and analysis of a Parkinson speech dataset with multiple types of sound

- recordings." *IEEE Journal of Biomedical and Health Informatics* 17.4 (2013): 828-834.
- [6] Muhammad Yusuf R. Siahaan, Rakhmad Arief Siregar, Faisal Amri Tanjung. (2023). Optimized Flexural Strength of Aluminium Honeycomb Sandwiches Using Fuzzy Logic Method for Load Bearing Application. *International Journal of Intelligent Systems and Applications in Engineering*, 11(4s), 466–472. Retrieved from <https://ijisae.org/index.php/IJISAE/article/view/2704>.
- [7] Lahmiri, Salim, and Amir Shmuel. "Detection of Parkinson's disease based on voice patterns ranking and optimized support vector machine." *Biomedical Signal Processing and Control* 49 (2019): 427-433.
- [8] Panda, Archana, and Prachet Bhuyan. "Machine Learning-Based Framework for Early Detection of Distinguishing Different Stages of Parkinson's Disease." *Specialusis Ugdymas* 2.43 (2022): 30-42.
- [9] Mr. Dharmesh Dhaliya, Dr.S.A.Sivakumar. (2019). Analysis and Design of Universal Shift Register Using Pulsed Latches . *International Journal of New Practices in Management and Engineering*, 8(03), 10 - 16. <https://doi.org/10.17762/ijnpme.v8i03.78>.
- [10] A. J. Lim and Y. H. Lee, "A Review of the Assessment Methods of Voice Disorders in the Context of Parkinson's Disease," in *Proceedings of the 12th International Conference on Biomedical Engineering*, 2019, pp. 602-608.

