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Machine Learning Based Idiopathic Parkinson's Disease Detection Using Speech Data

Mafas Raheem

Academic, School of Computing, Asia Pacific University of Technology & Innovation, Kuala Lumpur, Malaysia.

Abstract

The World Health Organization (WHO) has identified neurodegenerative disorders as one of the critical threats to public health. Currently, it is estimated that 16 out of 60 people suffer from neurological related diseases. Parkinson's disease is one of the most serious neurological diseases since there is no exact cure as yet. It is also referred to as Idiopathic Parkinson's disease since there is no reliable cause for the disease. Speech impairments analysis has been used as an efficient tool for the early detection of Parkinson's disease. Voice or speech can be a reliable biomarker for Parkinson's disease since 90% of Parkinson's disease patients normally experience hypokinetic dysarthria. There are several problems associated with Parkinson's disease such as there are obstacles to early diagnosis of Parkinson's disease, lower efficiency of the existing diagnosis method and expensive cost for the existing diagnosis. Machine learning has become a solution for detecting many types of diseases, and it can potentially be applied for the detection of Parkinson's disease as well. In this line, several commonly used machine learning predictive models were built and used speech data that can detect Parkinson's disease. Among the models, with the support of proper preprocessing and model tuning with cross-validation, the Deep Neural Network outperformed by obtaining 87.17% of accuracy with 0.88 of precision.

Keywords Parkinson's disease, Speech data, Machine Learning, Classification, Deep Neural Network.

Introduction

Parkinson's disease is one of the ubiquitous and progressive neurodegenerative diseases that affects around 1% of the total global population aged above 55 years (Nussbaum & Ellis, 2003). It ranks second in terms of most common diseases associated with a neurological disorder that negatively impacts the central nervous system and is just one place behind Alzheimer's disease (Ranjan et al., 2017). Parkinson's disease (PD) affects the brain cells that produce a chemical specifically a neurotransmitter known as Dopamine. Dopamine plays a major role in stimulating the coordination and the control of muscle activities by sending signals to the body muscles. Parkinson's disease attacks and deteriorates the brain cells, resulting in the decrease of dopamine production, which would lead to movement difficulties. Most Parkinson's diseases are considered Idiopathic Parkinson's disease since the cause for the disease is unknown.

Some typical symptoms of the disease include tremors in hands, stiffness in limbs during a movement, slowed & slurred speech which turns unmanageable, frequent loss of body balance and degradation in memory (Sonu, et al., 2017). Nearly 90% of individuals with Parkinson's disease have speech disorders known as dysarthria. Dysarthria happens when the vocal cords and muscles used for speech weaken, which causes difficulties to control them (Mayo Clinic, 2021). Therefore, it is normally associated with instabilities or inconsistencies in speech and low accuracy of voice, including decreased in loudness of the vocal, monotone occurrences, imprecision when pronouncing vowels and consonants, as well as irregular pauses or long gaps between sentences (Moya-Galé & Levy, 2019). The symptoms of Parkinson's disease worsen with time and thus early prediction of the disease is very crucial. At present, various machine learning techniques significantly contribute to predicting different diseases with high efficiency.

Machine learning is referred to as an application that helps computer programs to learn automatically and improve from experience with no explicit programming involved. In the medical field, machine learning helps speedy diagnosis as compared to traditional methods. Furthermore, the prediction of Parkinson's disease progression will also help in reducing the neurological problems among the patients and allow them to receive proper treatment in advance. In this paper, the researcher has taken the suitable application of the machine learning models to predict the Idiopathic Parkinson's Disease using speech data where the baseline speech features of the dataset were used for the prediction, which has never been significantly attempted so far.

Problem statement

Until today, Parkinson's disease does not have any highly reliable identified causes. Therefore, it is very strenuous to detect whether an individual is contracted with the disease at early stages or not until observed via visible symptoms. Moreover, there are no exact laboratory biomarkers to facilitate Parkinson's disease detection. Even though brain imaging scans like MRI (Magnetic Resonance Imaging) do not assure a diagnosis that in the end is considered as decisive (da Silva et al., 2018). Since there is no absolute cure for Parkinson's disease, early diagnosis becomes highly critical for patients contracted with the disease in terms of receiving the most effective and appropriate treatment.

The usual clinical diagnosis of Parkinson's disease heavily relies on the indication of two or three motor symptoms including the muscles stiffness in several parts of the body, presence of tremors even in the resting state of the body, noticeable reduction of the body movement speed and body-balancing difficulties. The typical tool utilized for identifying the disease symptoms is named the Unified Parkinson's disease rating scale (UPDRS), which requires high clinical expertise and experience. The method involving UPDRS can be used for identifying Parkinson's disease with an accuracy of up to 90%, but it averagely consumes 2.9 years for achieving a successful diagnosis (da Silva et al., 2018). This proves that the method is time-consuming, and the assessment is subjective. Besides that, patients are also required to be physically present in the medical centre for the diagnosis, which leads to inconvenience for individuals who are living in distant areas. Sometimes patients tend to develop numerous behavioural "tricks" in their movement to overshadow the actual movement that exhibits the real characteristics of Parkinson's disease, causing the accuracy and the reliability of the traditional clinical diagnosis to be even lower. Thus, an objective, easy in terms of accessibility, high reliability and simple to use diagnostic method is necessary for Parkinson's disease diagnosis (Tsanas et al., 2012).

Machine learning techniques that have the capability of effectively detecting Parkinson's disease could be applied to substitute the expensive diagnosis methods. The speech data is important in the implementation of machine learning methods in detecting Parkinson's disease. The ability of the human ear might have limitations in distinguishing the voices of healthy individuals from Parkinson's disease patients, but a computing device can be trained to carry out complicated and difficult tasks (Telkes et al., 2018).

This paper aims to build/propose a more effective and unbiased machine learning predictive model to facilitate the detection of Parkinson's disease at early stages based on speech features.

This paper has been arranged in ascending order by comprising Literature Review, Methodology, Data Analysis, Results and Discussion, and Conclusion.

Related Work

Introduction

Parkinson's disease is one of the neurological disordered conditions that impact people's life. The presence of these neurodegenerative disorders negatively impacts the body, mind that consequences as tremors in the hand, lacking control over fine motor skills, and degenerative speech situations (Tiwari & Singh, 2020). Prediction of Parkinson's disease is very strenuous as multiple tests are needed. In recent days, the vocal pattern test, and the spiral test, have been applied to enhance the accuracy of the diagnosis process. Several studies recommend the use of clinical trial design to obtain the diagnostic results in Parkinson's disease (Rastegar et al., 2019). The uncertainty of Parkinson's disease progression together with the lack of appropriate biomarkers makes the disease more threatening.

Usually, the most accurate predictions of Parkinson's disease are obtained using the Random Forest algorithm. This has also helped in gathering the frequency domains of the patients who are suffering from Parkinson's disease. Additionally, the study helps in finding the exact level of Parkinson's in patients by which accurate treatments can be proposed in the early stages of the patients. Early treatments, such as Levodopa or other speech therapies, halt the patients' health deterioration and improve the quality of life among the patients. Machine learning can help in detecting the disease at a faster pace and accuracy. This also helps in monitoring the disease among the patients with the regular diagnosis.

Significance on Early Detection

A precise prevalence of Parkinson's disease around the world is hard to be determined accurately. Hence, an estimate highlights the number of patients that are currently diagnosed with Parkinson's disease in the United States exceeds 1 million and is expected to rise to 1.2 million by 2030 (Parkinson's Foundation, 2021). Further, more than 10 million people are living with Parkinson's disease around the world (Parkinson's Foundation, 2021). The costs per year incurred for Parkinson's Disease in the United States have been estimated at close to USD 11 billion, which includes USD 6.2 billion in direct costs (O'Brien et al., 2009). Moreover, the largest amount of costs incurred for Parkinson's disease takes place in the middle or even later stages of the disease, where the motor symptoms are at their highest severity (Jack & Chen, 2010). Therefore, early detection of Parkinson's disease is more cost-effective as the capability in controlling the symptoms of the disease during earlier stages would significantly be helpful.

The impact of Parkinson's disease is considered as one of the most concerning and critical on a patient's quality of life (QoL) compared to all chronic diseases. The symptoms with the highest severity take place more progressively, strategies intended for early detection as well as treatment of the disease have great potential (Gage et al., 2003). In present days, the diagnosis of Parkinson's disease depends on the identification of motor symptoms that are visible and the patient's response towards specific medication such as levodopa. In post-mortem studies, it was discovered that there is a reduction of approximately 66% neurons in the brains of individuals contracted with Parkinson's disease when compared with the neurons of healthy individuals (Pakkenberg et al., 1991). These figures defined an extensive range, even though it should be specified that the assumption is generally held that dopamine neuronal loss of around 60% to 80% creates the threshold at which symptomatic disease happens.

However, substantial neurological damage happens to take place when motor symptoms appear. Therefore, early treatment of Parkinson's disease is very difficult to achieve due to the nature of diagnosis which is mostly clinical. This means that patients can get diagnosed with Parkinson's disease via clinical means only when motor symptoms of the disease become visible (Michela et al., 2016). Therefore, machine learning techniques have the potential and capability to significantly change the diagnostic landscape in the upcoming future, making the early diagnosis as well as treatment achievable.

Speech Impairments as a Pre-Motor Symptom

Parkinson's disease is not merely a disease associated with the central nervous system, but the peripheral nervous system seems to play a significant role especially in the early stages. Most of the pre-motor symptoms that arise in early stage emerge in peripheral nervous system structures. The manifestations of pre-motor symptoms in Parkinson's disease vary as they affect sensing smell, gastrointestinal, urinary function, mood, sleep, and a diversity of cerebral activities such as memory and attention (Michela et al., 2016). Some typical non-motor symptoms include urinary dysfunctions, sexual dysfunctions, and mood disorders.

Even though motor symptoms are the most identifiable of Parkinson's disease, non-motor symptoms are important too as they represent not only a large percentage of overall Parkinson's symptoms but also, in numerous cases, they appear earlier as compared to motor symptoms and have been proved to exert a more severe negative impact on quality of life as compared to motor symptoms (Michela et al., 2016). The non-motor symptoms could possibly be present in an individual for up to ten years before diagnosed. Therefore, in spite of the fact that the typical Parkinson's disease still heavily depends on motor symptoms, pre-motor symptoms hold a promising potential regarding the early diagnosis of Parkinson's disease.

One of the most common pre-motor or non-motor problems that 90% of individuals suffer from idiopathic Parkinson's disease is voice impairment or speech disorders (Ang, 2018). Studies have shown that individuals contracted with Parkinson's disease are likely to develop hypokinetic dysarthria (Parkinsonian dysarthria), where the individuals face problems with their voice and speech production (Ramig et al., 2007). Hypokinetic dysarthria occurs when there is a reduction in the movements of the larynx which is caused by insufficient activation of the muscles. Research conducted by Ramig et al. (2007) proved that there are nearly 90% of individuals with Parkinson's disease showed deficits or impairments in speech, which consequently led to raising of a critical alert to the problem. Typical symptoms in hypokinetic dysarthria include hypophonia which leads to softness in speech, dysprosody (monotone in speech), slurred speech contributed by imprecise articulation occurrence of tremors in the voice where the voice quality becomes breathy and hoarse (Ang, 2018). Besides that, inactive movements in the lungs and respiratory systems cause breathing issues (Buetow et al., 2013).

There are several significant impacts on the patients due to speech impairments which include impacts regarding interaction with other individuals, conversation difficulties, feelings of intelligibility and the voice effect (Ang, 2018). To be more specific, the condition may lead to frustration and eventually causes the patients to avoid regular conversations as well as social activities, which then increases the risk concerning the development of psychological related disorders, for instance, depression and anxiety that will ruin the quality of life (Ramig, 2007). Speech or voice data is expected to be 90% helpful in terms of diagnosing an individual in identifying the presence of Parkinson's disease patients affected by dysarthria (Anila & Pradeepini, 2020).

Significance of Machine Learning in Neurological Disease Prediction

Big data is defined as a large volume of data that is being collected, yet the data is not valuable unless it is being utilized properly, which is where machine learning methods can be applied to obtain useful insights to draw valid conclusions. Machine learning application in the healthcare domain is increasing and improving tremendously. In recent years, there is a rapid growth in machine learning implementation in the field of neurological ailments such as Alzheimer's disease, Amyotrophic Lateral Sclerosis (ALS) and Parkinson's disease. The effort of implementing machine learning methods on neurological diseases prediction is still a great challenge since it is very difficult to understand the mechanism of the complex brain and there are uncertainties due to the deficiency of suitable tools for analysis (Janga & Reddy, 2017).

There are requirements for better diagnosis methods that can predict Parkinson's disease. Moreover, machine learning can be utilized for the early detection of Parkinson's disease and state possible cures for the disease. It can be implemented to prevent the misdiagnosis that often takes place in Parkinson's disease due to the occurrence of cognitive biases by humans (Miller & Brown, 2018). Therefore, the importance of predicting Parkinson's disease with the application of machine learning has been focused on in this study.

Review on classification techniques used in prediction of Parkinson's disease

The application of data mining techniques especially predictive analytics has become more rigorous in the healthcare domain in the recent past. The application has captured vast sub-domains of health care such as diabetes, cancer, heart/kidney failure etc. A significant number of research works has been reviewed that employed machine learning algorithms to predict Parkinson's disease using different types of data.

Athanasios et al. (2012) implemented Random Forest and Support Vector Machine models using 263 samples from 43 subjects, reaching almost 99% overall classification accuracy using only 10 dysphonia features. The features were selected using four feature selection algorithms with a smaller number of samples to obtain the mentioned accuracy. Sakar et al. (2013) utilized a wide variety of voice samples and various sound types, including sustained vowels, words, and sentences compiled from a set of speaking exercises. As per the analysis, the authors explored that the sustained vowels were found to carry more PD-discriminative information than the isolated words and short sentences where KNN with K=1 obtained 82.50% accuracy and SVM linear kernel obtained 85% accuracy.

Benba et al. (2015) worked on Detecting Patients with Parkinson’s disease using Mel Frequency Cepstral Coefficients and Support Vector Machines using 34 sustained vowels from 34 subjects including 17 PD patients. The Mel Frequency Cepstral Coefficients (MFCCs) from each individual were extracted from 1 to 20 coefficients. The best classification accuracy achieved was 91.18% using the first 12 coefficients of the MFCCs by Linear kernels SVMs using the Leave-One-Subject-Out (LOSO) validation scheme. Aarushi et al. (2016) proposed an approach using Extreme Learning Machine (ELM) for predicting Parkinson’s disease with the reliable dataset from the UCI repository. Their proposed model acquired an accuracy of 81.55% on the testing data claiming to be better than the existing models such as Neural Network and Support Vector Machine.

Tiwari (2016) used a minimum redundancy maximum relevance feature selection algorithm to select the most important feature to predict Parkinson’s disease. The author found that the Random Forest model obtained an overall accuracy of 90.3% on 20 features with a precision of 90.2% and ROC values 0.96 claimed as the highest as compared to other machine learning models such as random forest, rotation forest, random subspace, support vector machine, multilayer perceptron, and decision tree-based methods. Zeng et al. (2016) proposed a method to detect Parkinson’s disease using gait analysis (gait patterns of healthy controls and Parkinson’s disease patients) via deterministic learning theory using Radial Basis Function (RBF) neural networks. 93 patients and 73 healthy controls were classified with a five-fold cross-validation method using the gait patterns and obtained an of accuracy 96.39%.

Dinesh and Jennifer (2017) found that the Boosted Decision Tree as the best model with an accuracy score of 91-95% using extrapolated data from voice recordings of Parkinson's patients and unaffected subjects including nonlinear measures of fundamental frequency variation in the voice recordings. Karabayir et al. (2020) used “Parkinson Dataset with Replicated Acoustic Features which included 44 speech-test based acoustic features from Parkinson’s disease patients and controls. Various machine learning algorithms including Light and Extreme Gradient Boosting, Random Forest, Support Vector Machines, K-nearest neighbourhood, Least Absolute Shrinkage and Selection Operator Regression, as well as logistic regression, were implemented. Light Gradient Boosting as the best model obtained an AUC of 0.951 with a 95% confidence interval 0.946–0.955 in 4-fold cross-validation using only seven acoustic features.

On the whole, the application of Neural Network has been sighted less significantly such as Artificial Neural Network, Deep Belief Network, Restricted Boltzmann Machines, Back Propagation algorithm, Probabilistic Neural Network and Deep Neural Network with various accuracy values using Speech data (Anila & Pradeepini, 2020). However, the crucial aspects such as feature engineering, feature selection, class balancing and so on were not significantly reported. Various and commonly used machine-learning algorithms were implemented in this paper by applying the most suitable preprocessing and optimization techniques in finding the most suitable hyperparameters to choose a more lucrative predictive model at the end.

Methodology

Generally, a methodology acts as an outline for demonstrating how the tasks are being planned, managed, and performed in a project. In a data science project, it is vital to manage every stage to make sure that the correct methods or techniques are applied throughout to guarantee success (Zavgorodniy, 2018). The methodology selected for this project is Cross-Industry Standard Process for Data Mining (CRISP-DM which provides high flexibility by allowing processes or tasks to be improved regularly during the succeeding iterations (Usman & Mafas, 2020). Moreover**,** CRISP-DM enables the creation of a long-term strategy based on short and quick iterations in the early development of data science projects spread across six phases such as business understanding, data understanding, data preparation, modelling, evaluation, and deployment (Rodrigues, 2020).

The business understanding phase mainly focuses on the understanding of the right problem. It is crucial to select data analytics tools/machine learning algorithms required to successfully achieve the set objectives. The data understanding phase starts with the investigation of different data sources and choosing the more suitable one where a rough estimation of the number of data required is apt (Studer et al., 2021). This may include descriptive analytics of the data to decide some crucial pre-processing tasks.

The data preparation phase is usually time-consuming where it occupies up to 80% of the overall time taken for a data science project. Data preparation occurs after the problem is clearly understood and the data available are explored. This phase comprehends data integration, data cleaning, data wrangling, feature selection as well as feature engineering. The data modelling phase involves the development and assessment of suitable predictive model(s) based on the implementation of diverse modelling techniques. Therefore, various, and commonly used machine-learning algorithms were implemented in this regard.

The evaluation phase focuses on evaluating the degree to which the developed model(s) meet the objectives of the project. The models are generally evaluated based on the type of data mining technique used. In this study, the evaluation measures such as accuracy, precision, recall and F1 score are taken into consideration. The final phase is model deployment. The most effective machine learning predictive model that has been built and evaluated via suitable performance measures would be prepared for the production environment. A suitable deployment plan can be drafted comprising operational details when an adequate request is met. This stage is not discussed in this paper as this fall under the operationalization of the model.

Data Analysis

Data Understanding

The data titled “Parkinson’s Disease Classification Data Set” was acquired from a well-known and reliable open data repository named UC Irvine Machine Learning Repository (UCI) as shown in Table 1. The original dataset has 756 records and 24 attributes, where the class variable indicates whether an individual is contracted with Parkinson’s disease (binary outcome = 1) or not (binary outcome = 0).

Table 1: Data Description

No	Attribute Name	Attribute Description
1.	id	Subject ID
2.	gender	Gender
3.	PPE	Pitch Period Entropy
4.	DFA	Detrended Fluctuation Analysis
5.	RPDE	Recurrence Period Density Entropy
6.	numPulses	Number of Pulses
7.	numPeriodsPulses	Number of Period Pulses
8.	meanPeriodPulses	Mean of the Period Pulses
9.	stdDevPeriodPulses	Standard Deviation of the Period Pulses
10.	locPctJitter	Local Jitter measured by Percentage
11.	locAbsJitter	Local Absolute Jitter
12.	rapJitter	Relative Average Perturbation Jitter
13.	ppq5Jitter	Jitter which focuses on the Perturbation Quotient of Period in Five Point
14	ddpJitter	Jitter which focuses on the Difference of Differences of Periods
15	locShimmer	Local Shimmer
16	locDbShimmer	Local Decibel Shimmer
17	apq3Shimmer	Shimmer focusing on the Quotient of Amplitude Perturbation in Three Point
18	apq5Shimmer	Shimmer focusing on the Quotient of Amplitude Perturbation in Five Point
19	apq11Shimmer	Shimmer focusing on the Quotient of Amplitude Perturbation in Eleven Point
20	ddaShimmer	Shimmer which focuses on the Difference of Differences of Periods
21	meanAutoCorrHarmonicity	Mean of Harmonic Autocorrelation
22	meanNoiseToHarmHarmonicity	Mean of the Noise to Harmonics Ratio
23	meanHarmToNoiseHarmonicity	Mean of the Harmonics to Noise Ratio
class	Class of the Subject or Individual	0 - Healthy 1 - Contracted with Parkinson’s disease.

The dataset was found with no missing values with an imbalanced class.

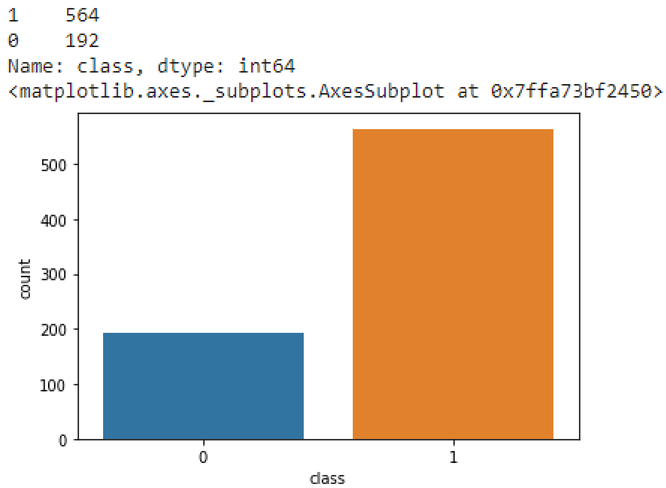

Figure 1: Class level distribution

According to Figure1, the target variable seems highly imbalanced, thus was handled during the pre-processing.

The standard correlation coefficient or commonly known as Pearson's correlation between all the variables with the target variable was explored as a correlation heat map as shown in Figure 2.

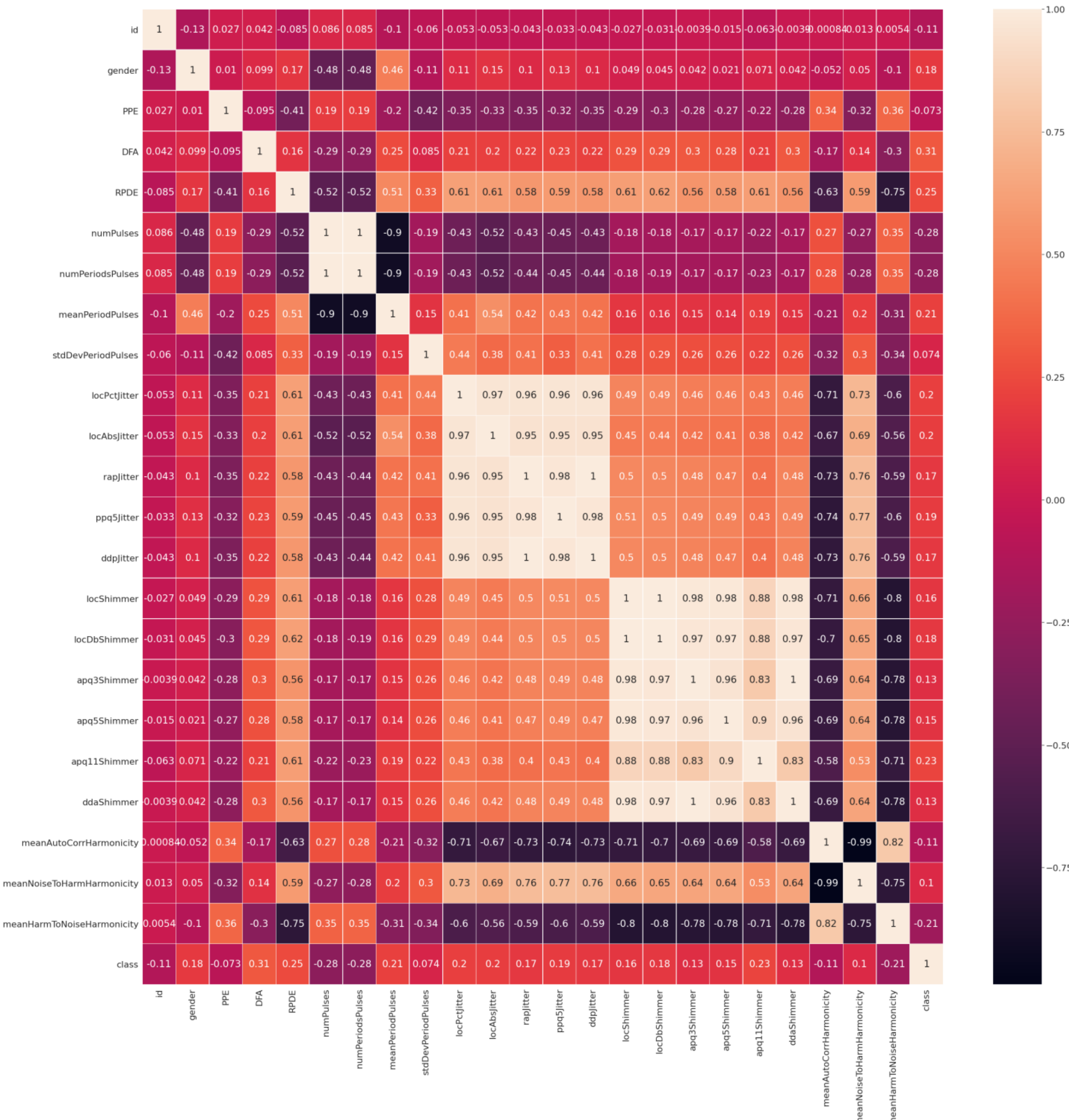

Figure 2: Correlation Heat map

According to the correlation heat map, one of the input variables that are highly correlated were dropped for the model building process in the pre-processing stage. Further, data transformation was also performed to get the data more suitable for the model building.

Pre-Processing

Feature Selection

The more impactful features were selected by filtering the high correlated input variables. The selected variables were as follows:
'gender', 'PPE', 'DFA', 'RPDE', 'numPulses', 'meanPeriodPulses', 'stdDevPeriodPulses', 'locPctJitter', 'locShimmer', 'meanAutoCorrHarmonicity'

The selected variables seem to be more impactful in predicting the contraction with Parkinson's disease.

Class Balancing

Handling imbalanced classes in a dataset is a very crucial task as it may lead to having a biased result. Two methods can be used to handle imbalanced classes such as under-sampling and oversampling. As the dataset contains fewer amount data, oversampling using the SMOTE (Synthetic Minority Oversampling) technique was applied to balance the class (Figure 3), which is an ideal oversampling method to increase the data points for minority classes via the augmenting data with identical data points as of the minority class (Patel, 2020).

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Counter({1: 564, 0: 564})
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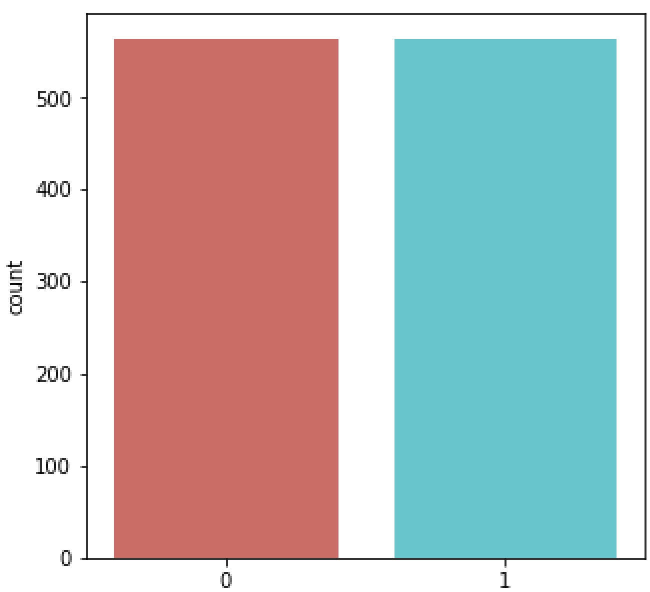

Figure 3: Balanced class level distribution

Data Transformation

Data transformation has been understood as the process of converting the data into a more useful format. The MinMaxScaler function was used in this regard.

Data Split

Data split is yet another crucial activity in the process of predictive model building. In this project, the data was split was done as 80% for training and 20% for testing while applying the random selection.

Modelling

Select Modelling techniques

Choosing the right machine learning algorithms to build effective predictive models is very crucial in any data science project. A methodical way is more appropriate in this regard as shown in Fig. 4. The selection could be from the experience or literature review or both. In this paper, the commonly used machine learning algorithms were selected based on the literature. Therefore, several supervised modelling techniques such as Deep Neural Network, Extreme Gradient Boosting, Random Forest, Extra Tree Classifier, Gradient Boosting, Support Vector Machine, AdaBoost Classifier, Decision Tree and Logistic Regression were selected for this purpose.

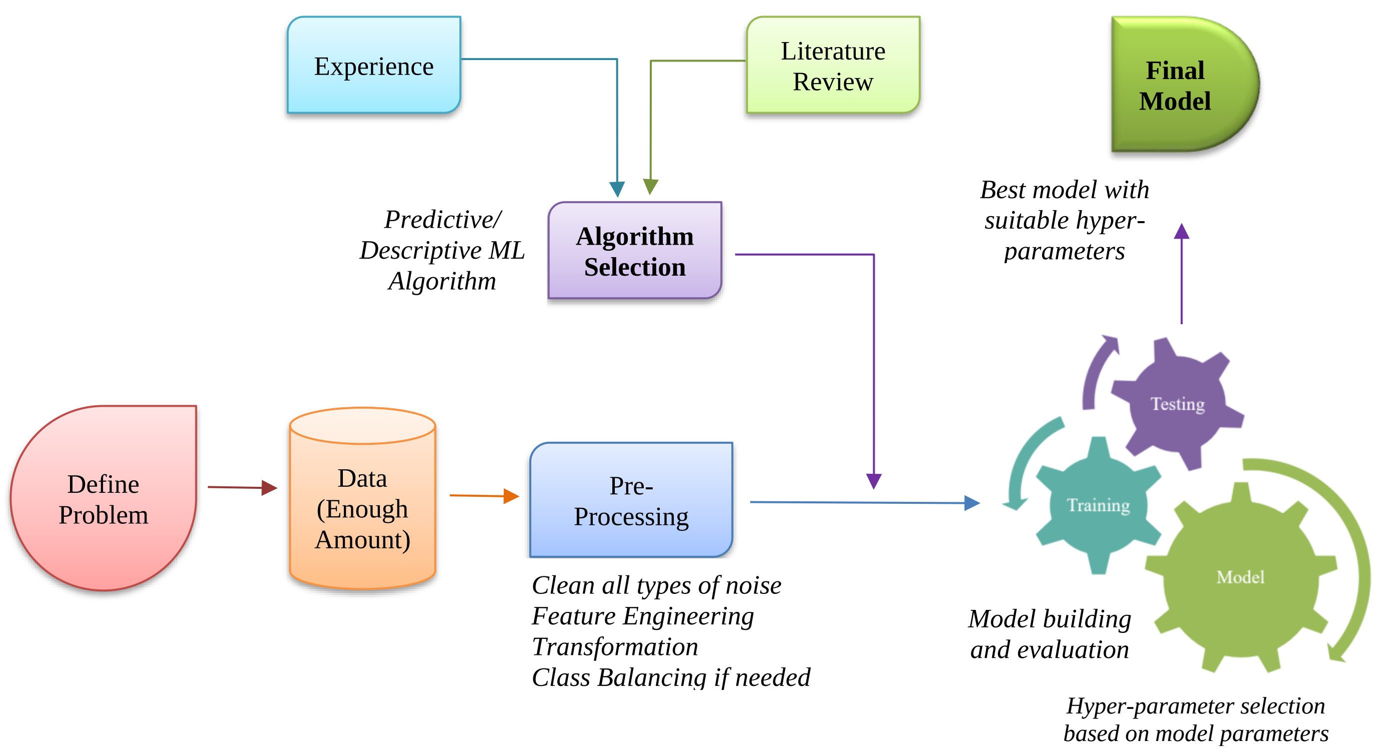

Figure 4: Optimal model building process

Model Building

The machine learning predictive models were built using the defined train dataset where a set of hyperparameters were used to tune the models. The model tuning was done using the GridSearchCV method with 5-fold cross-validation. However, the Deep Neural Network model was tuned explicitly for different hyperparameters which are tabulated and discussed below. As per the tuning procedures, the optimal hyperparameters chosen are tabulated in Table 2:

Table 2: Predictive Models with optimal hyperparameters

Model	Hyperparameters	Values
Deep Neural Network (DNN) using Keras-Tensorflow	kernel_initializer	lecun_uniform
	activation	relu for input and hidden layers sigmoid for output layer
	optimizer	adam
	loss	binary_crossentropy
	metrics	accuracy
	Dropout	0.2
	batch_size	32
	epochs	200
	Hidden Layer Neurons	Layer 1 = 1000 Layer 2 = 500 Layer 3 = 300
Extreme Gradient Boosting	colsample_bytree	0.6
	gamma	0.1
	max_depth	7
	min_child_weight	1
	reg_alpha	0.001
	subsample	0.8
Random Forest	Bootstrap	False
	class_weight	balanced
	criterion	entropy
	max_depth	80
	max_features	sqrt
	min_samples_leaf	1
	min_samples_split	2
	n_estimators	200
Extra Trees Classifier	criterion	gini
	max_depth	10
	max_features	log2
	min_samples_leaf	1
	min_samples_split	2
	n_estimators	400
Gradient Boosting Classifier	learning_rate	0.1
	max_depth	6
	n_estimators	100
	random_state	7
Support Vector Machine	C	1

	class_weight	balanced
	Degree	8
	Gamma	scale
	Kernel	poly
AdaBoost Classifier with Decision Tree Classifier as the base estimator	Decision Tree Classifier criterion = 'gini' max_depth = 36 max_features = 'auto' min_samples_leaf = 1 min_samples_split = 2	
	learning_rate	0.0001
	n_estimators	10
	random_state	2
Decision Tree Classifier	criterion	entropy
	max_depth	24
	max_features	auto
	min_samples_leaf	1
	min_samples_split	2
Logistic Regression	C	9
	class_weight	balanced
	random_state	0
	solver	liblinear
	tol	1e-05

Results and Discussions

The predictive models were built using the speech data with careful executions of the pre-processing activities. The results obtained from the machine learning predictive models were discussed in detail from a technical perspective. The discussion mainly focused on the results of the models via the performance evaluation measures such as accuracy, precision, recall and F1 Score. All the predictive models were built via an unbiased treatment to obtain the most suitable results. Figure 5 displays the performance measures of the machine learning predictive models in terms of accuracy. According to the obtained accuracy values, the Deep Neural Network model obtained the highest accuracy of 87.17% and the model also obtained 0.88 as the precision. Exclusive model tuning was done on the selected hyperparameters and chosen the model with the most optimal combinations as shown in Table 2. However, the accuracy values of the other models were significant compared to the models built in the past with all the crucial pre-processing activities.

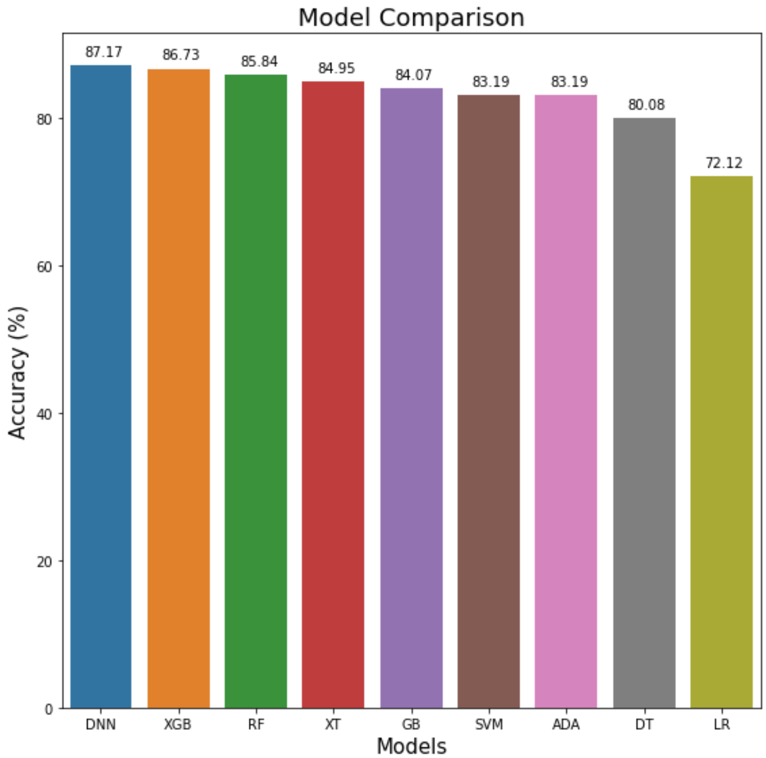

Figure 5: Accuracy values of the predictive models

Deep Neural Network as the best performing model obtained an accuracy of 87.17% with the best combination of the hyperparameters tabulated in Table 2. Further, the model's confusion matrix along with the classification report has been showcased in Figure 6.

```
Confusion Matrix:
 [[102   8]
 [ 21  95]]

 Clasification Report:
               precision    recall  f1-score   support

           0       0.83      0.93      0.88       110
           1       0.92      0.82      0.87       116

    accuracy                           0.87       226
   macro avg       0.88      0.87      0.87       226
weighted avg       0.88      0.87      0.87       226
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Figure 6: Classification report of DNN

Conclusion

No doubt detecting Parkinson's disease via machine learning methods has become an interesting and more significant research area as the early detection of the disease can improve the quality of a person's life. Parkinson's disease is usually extremely strenuous to diagnose at the beginning. However, speech changes that are caused by Parkinson's disease can be detected by advanced machines even though the disease is still in its early stages. Few studies have proven that speech or voice-related data has high reliability as well as effectiveness for Parkinson's disease identification. The Discovery of a solution to distinguish Parkinson's disease patients and healthy people by implementing various vocal tests often ends up with lower accuracy as all the voice samples are included to be handled by only one classifier. In this paper, a dataset that contains the values that are being displayed after analysis of patients', as well as healthy individuals' voice recordings, is being retrieved for the prediction. Out of all the models built, DNN outperformed with the accuracy of 87.17% with carefully implemented pre-processing tasks. DNN is a black box technique where the architecture won't reveal any insights or easy interpretation of the results to the decision-makers except the model accuracy and other evaluation measures. In this line, building a DNN with many hidden layers and tuning it to obtain a promising result in the healthcare domain is challenging too. The model with the highest accuracy can assist doctors to identify patients with Parkinson's disease in the future.

Future Enhancements

To facilitate further improvements of the machine learning models, more Parkinson's disease-related data would be helpful to obtain more accurate models. Other types of datasets such as the finger tapping dataset can also be integrated with the voice data for the prediction if it is compatible.

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