Survey of Parkinson's Disease Detection Methods

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Abstract—**Parkinson's disease (PD) is one of the degenerative diseases that seriously affect people's lives. It occurs when there is death of dopamine producing neurons in the substantia nigra, one of the central nervous systems (CNS) components. People with Parkinson's disease have impairments in their speech, writing, and walking. In recent years, there have been studies that have used gait and even EEG recordings for PD detection. However, the most studied area has been in speech. It has been shown that out of all the PD patients, 90% have been found to have speech impairments. Voice deterioration is one of the most prominent voice changes that occur with worsening PD. Voice analysis is one of the many noninvasive voice treatments that have been shown to improve the quality of life of patients. Therefore, speech analysis has attracted a great deal of attention for the development of tele-monitoring and tele-diagnosis predictive models. The accurate analysis of speech has been one of the most challenging problems in the classification of PD. The primary objective of this paper is to review the application of machine learning and deep learning methods for the classification of Parkinson's disease. The methods of machine learning and deep learning have been employed in the quest for more efficient ways to classify Parkinson's disease (PD). Examples of such classification methods include support vector machines, naive Bayes, deep neural networks, decision trees, and random forests. In reviewing the results of various studies, both machine learning and deep learning algorithms have proven to be very useful and have provided a better means to identify Parkinson's disease in its early stages. The classification accuracy attained by the machine learning classifier. Out of all the deep learning methods, the deep neural network has the highest accuracy of 99.49%. The varioud studies have shown that artificial intelligence has become a powerful tool for learning and has a lot to be offered to both data science and neurology. Overall, the methods of learning have proven to be very useful in solving decision making problems which is particularly true in the area of medical diagnosis.**

Index Terms—**Deep neural network, Parkinson's disease, speech.**

I. INTRODUCTION

Parkinson's Disease (PD) involves the progressive degeneration of the central nervous system, impacting motor control [1]. PD is the second most common neurological disorder, coming after Alzheimer's Disease, with more than a million recorded cases in North America [3]. PD has also been known as shaking palsy, a term coined by Dr. James Parkinson in 1817 [4]. Due to the rapid increase in PD among those aged 60 and above, the number of cases is expected to rise with the aging population [5][6].

Loss of specific clusters of neurons that release certain neurotransmitters, including acetylcholine, dopamine, norepinephrine, and serotonin, is the start of the pathology of PD. The absence of dopamine, in particular, is responsible for the onset of urinary and visual issues, anxiety and depression, panic attacks, and weight loss [6]. Other PD symptoms include voice loss, impaired balance, and tremor [7]. Research studies have shown that the majority of PD patients, more than 90%, experience some speech and voice disorders [8][9], including, among others, dysphonia, and dysarthria, and they may present with hypophonia [10]. Therefore, the first, and often the only, noticeable symptom in Parkinson's patients is the voice impairment [11]. Patients with Parkinson's also experience abnormalities in the REM phase of their sleep [12]. As of now, the the exact etiology of the disease is unknown [13][14]. However, in the early stages of the disease, there are proven pharmacological therapies which can alleviate the symptoms to some extent. Voice analysis, being easily accessible and non-invasive, has the potential to be used in the monitoring of the progression of PD [15][16]. Numerous vocal assessments have been developed for this purpose.

These include prolonged phonation as well as running speech text [15][16]. Telediagnosis and telemonitoring systems are already established technologies used for early stage PD detection. Most of these techniques focus on motor symptoms which are present due to PD.

Typically, PD diagnosis follows three steps: 1) data pre-processing, 2) feature extraction, and 3) classification. For the first step, the voice signals are segmented using time-windows. The speech signals are then subjected to filtering to remove the noise present within the anaysis. Several features are extracted from each segment in the second stage. Classification occurs during the last stage. The choice of method for feature extraction is critical, especially in the case of classification, as it determines how well the PD is diagnosed. This paper aims to present the various machine learning (ML) and deep learning techniques used for diagnosis of PD.

The paper is structured as follows: Section 2 reviews the literature on PD detection. Classification techniques and algorithms are discussed.

II. LITERATURE SURVEY

Numerous attempts have been made by various researchers over time to predict the occurrence of Parkinson's disease in individuals. This part provides a review of the literature on the work done to date.

Through the use of machine learning techniques, Little Max and colleagues [14] devised a new way of classifying subjects into PD and control subjects by the presence of dysphonia. Their study introduced a new robust measure of dysphonia, named "pitch period entropy" (PPE), which is a measure of dysphonia that works in uncontrolled and noisy environments. The study was conducted with a sample of 31 subjects, 23 of which were PD patients and the rest were healthy. They pronounced 195 sustained vowels. The subjects' ages were in the 46-to-85-year range. Each subject was recorded for 6 phonations. The features were filtered, and from the 10 most correlated measures, all possible combinations were evaluated. It was determined that 4 of the measures in that combination yielded the best classification. Their proposed method reported an accuracy of 91.4%. They state that the best classification results are obtained by combining traditional harmonics and noise ratios (HNR) with atypical methods.

Different classification techniques for PD diagnosis were evaluated by [19]. PD detection involved classifiers based on software from SAS. The classifiers were neural decision trees, neural networks, and regression. The accuracy achieved was 84.3% for DM: neural, 88.6% for regression, 84.3% for decision trees, and the highest at 92.9% for neural networks. The dataset was split into 65% for training and 35% for testing. The hyperparameter tuning was conducted independently for each of the classifiers. LM (Levenberg-Marquardt) algorithms were implemented in the study.

In [21], subjects were suggested as normal from subjects with Parkinson's Disease (PD). In this case, the dimension of the feature vector was reduced, and the optimized features were obtained through the application of a genetic algorithm (GA), while k-nearest neighbor (k-NN) was employed for the purposes of classification. In this study, the Parkinson's dataset [121], which is located in the UCI repository, consists of 197 voice samples recorded from 31 subjects, of which 23 were PD patients, and 8 were normal subjects.

B. E. Sakar et al. (Lioj) proposed a model for separating subjects into control and PD subjects. For their research, data was obtained from 40 subjects (20 PWP and 20 healthy). Each participant was tasked with recording 26 voice samples comprising words, short sentences, numbers, and sustained vowels. SVM and k-NN along with 1 Summarized Leave-One-Out (s-LOO) and Leave-One-Subject-Out (LOSO) were used for classification and cross-validation, respectively. For model evaluation, the performance measure of accuracy and sensitivity was used. Along with those, specificity and Matthews's correlation coefficient (MCC) were also calculated. The Pratt acoustic analysis software was used for feature extraction. The k-NN classifier was tested with the values of k set to 1, 3, 5, and 7, while for SYM, linear and RBF kernels were used. The attained accuracy was 82.50% for k-NN and 85% for SVM.

Data mining algorithms were applied by Dr. R. Geetha Ramani et al. for classifying the control and PD subjects. Their study's dataset consists of 197 voice samples for which 22 features were extracted [21]. A number of different classification models were applied, which included a random tree (Rnd tree), k-NN, SVM, C4.5, IDJ, binary logistic regression, LDA, and PLS. For the random tree model, 100% accuracy was achieved and k-NN, C4.5, and LDA reported over 90% accuracy. The lowest accuracy of 69.74% was observed for the C-PLS algorithm

In a different study, David Gil A. et al. [23] proposed techniques based on SYM and artificial neural networks (ANN). The dataset was obtained from the UCI repository [21]. They used an ANN-based multilayer perceptron (MLP) network with one or two layers. SVM was found to offer statistically significant better results compared to MLP. The SVM with the linear mid-puk kernel achieved an accuracy rate of 91.79% and 93.33%, respectively, while the MLP reached an accuracy rate of 92.31%.

Psita Bhattacharya et al. [24] applied SVM, a type of supervised machine learning algorithm, to classify the PD subjects from the controls. The authors used Weka, a software tool for data mining. A data pre-processing step was undertaken on the dataset [2lj] prior to applying the classification algorithm,some data was manipulated, and the classification algorithm was randomly split multiple times, resulting in different kernel values applied libsm. It was found that the RBF kernel and the poly kernel SVM achieved the highest accuracy of 60.8696%, while the linear kernel SVM reported the best accuracy of 65.2174%.

To carry out the T11e classification, K. Uma Rani et al. [25] employed an RBF network alongside a multilayer perceptron. The dataset included 136 sustained vowel phonations, 83 of which were recorded from PD patients, while the other 53 were from healthy controls. Of the total recordings, 112 were utilized for training and 24 for testing. The authors observed that the RBF network outperformed the multilayer perceptron. The multilayer perceptron and RBF network achieved training set accuracies of 86.66% and 90.12%, respectively, and testing set accuracies of 83.33% and 87.5%, respectively.

Achraf Benba et al. [26] collected a dataset of 34 sustained vowels from 34 different subjects, 17 of whom have PD. From each subject, 1, 17 of whom to 20 Mel-frequency cepstral coefficients (MFCCs) were extracted. Various kernel types of SVM were applied, and the leave-one-subject-out validation method was used. The highest accuracy, 91.17%, was achieved by the linear kernel SVM, using only the top 12 MFCCs. In another of their works [27], they intended to classify persons with Parkinson's disease from those with other neurological disorders. They sampled voices of 50 subjects, 30 of whom were PD patients, while 20 were elderly patients with neurological disorders. Extracted from every voice sample, Cepstral coefficients were obtained through three cepstral approaches: MFCC, PLP (RASTA-PLP), and Perceptual Linear Prediction (PLP). Five supervised classifiers with different kernel types were employed. These included SVM and discriminant analysis, K nearest neighbor, naive Bayes, and classification tree (CT). The first 11 PLP coefficients achieved 90% accuracy with linear kernel SVM.

C.O. Sakar et al. [28] analyzed several algorithms in the field of PD detection in voice signal processing. For the first time, the TQWT was used to extract features from the voice signal. Other state-of-the-art techniques used to extract features from voice recordings of patients with Parkinson's disease were also TQWT compared. For the purpose of this study, voice recordings of 252 participants were taken, and a multitude of recordings were processed. Several classifiers were evaluated based on different features and predictions of the classifiers were combined through ensemble learning techniques. It was found that. MFCCs and TQWT contributed the most to the accuracy of the classifiers and that LL1US was significant to PD classification. In order to minimize redundancy and maximize correlation (MRMR) was used to select the most relevant features for the classification. The MRMR filter was used to select the 50 most relevant features on which different algorithms were run. The RBF kernel SVM achieved the highest accuracy of 86% on all feature subsets.

An algorithm for diagnosing Parkinson's disease was proposed Shabakhi [f29]. Of all the features extracted, the genetic algorithm determined the optimal features from the dataset [21]. Different numbers of optimized features were used for classification against SVM. For the sets of 4, 7, and 9 optimized features, the reported accuracies were 94.5%, 93.66%, and 94.22%, respectively.

Richa Mathur et al [30] proposed a method for predicting PD. They used a weka tool for the algorithms for the pre-processing of data classification and the result analysis on the given dataset [21]. They used k-NN with Adaboost. Ml, bagging, and MLP. Results showed that k-NN + Adaboost. Ml and k-NN + MLP achieved the same accuracy of 91.28% while the time for building the model with Adaboost. Ml was 0.01 and with MLP it was 0.43. Hence, k-NN + Adaboost. Ml is the best classification algorithm that produced remarkable results and was time saving. Amin ul Haq et al [311 proposed a classifier model that classifies the subjects into control and Parkinson subjects. In their study, they used the LI-norm SVM algorithm to select the relevant features and then classification was done. Their proposed system consisted of 1) data pre-processing, 2) selection of relevant features, 3) cross-validation (CV) and 4) evaluation of classifiers. 10-fold CV was applied for SVM (with both linear and RBF kernel). The highest accuracy of 95% and 97% were recorded on full features with RBF and linear kernel SVM, respectively.

An accuracy of 99% was reported from selecting the most relevant features. This shows that it is possible for a significant improvement of the classifier performance to be achieved through relevant features selection.

A new approach to identify the early signs of PD was developed by Diogo Braga et al [32] through analysis of speech. They implemented SVM, Random Forest, Naive Bayes, and Neural Network classifiers. In their approach, they used 3 different speech datasets. One was comprised of 22 PD patients, and it was the largest dataset, containing 1002 speech samples. The second smaller dataset, with 30 healthy controls, had 785 speech samples. The third dataset was used to validate the performance of the Machine Learning algorithms and consisted of sustained vowels from 28 PD patients. Using Random Forest + LOSO validation scheme gave an accuracy of 94.77%. After algorithm optimization, this improved to 99.94% with Random Forest. The SVM with RBF kernel and Neural Network achieved 92.38% and 91.10% accuracy respectively.

Another major contribution was made by Salama A. Mostafa et al. (33] who described a method based on multiple feature evaluation (MFEA) which identified 11 most relevant features. The classification algorithms NB, SVM, neural network, RF, and OT with 10-fold CV have been implemented. With respect to result analysis, two datasets have been used - the original dataset, and the dataset with the features filtered out. The original dataset yielded the neural network with the highest accuracy of 87.755%. In contrast, the dataset with filtered features yielded the random forest with 99.492% accuracy. NB, NN, decision tree, and SVM attained accuracy of 89.340%, 96.950%, 96.954%, and 95.431%, respectively.

In this study, Ozcift [34] applied the rotation forest (RF) ensemble technique combined with linear SVM feature selection to PD diagnosis. The dataset [21] comprises 195 voice samples from 31 subjects, 23 of which were PD patients. The dataset contains 22 speech features. The method proceeded as follows. Initially, the 22 attributes were reduced to 10 using linear SVM. In the next step, six different classification algorithms were applied to a feature subset. The last step involved the application of ensemble method RF of \[IBk\] (a variant of k-NN) to boost model improvements. Several different metrics were used to measure the performance of classification including Kappa, Error, classification, and accuracy. The highest accuracy (96.93%) was achieved using \[IBk\] and the lowest (88.71%) was achieved using REF kernel SVM.

I. Nissar et al. [36] utilized an ensemble machine learning approach to classify PD. For their framework, they conducted data pre-processing on a first dataset [291 that involved data normalization and subsequent feature relevance analysis. The data was normalized using the min-max method. RFE and MRMR were employed to determine relevant features. The selected relevant features were then used to train the classifiers to complete the task. For performance analysis, they considered nine different machine learning algorithms. Among all the classifiers, XGBoost combined with the MRMR feature selection method achieved the highest accuracy of 95.39% and a precision, recall, and F1-score of 0.95, 0.95, and 0.95, respectively, when both MFCC and TQWT features were included.\'

C.D. Anisha et al. [37] used the dataset in [29] where they applied the LDA and PCA methods to identify the highly correlated features. Ensemble classifiers such as Gradient Boosting Machine (GBM), Extreme Gradient Boosting (XGBoost), Baging and AdaBoost (called AdaBoost) were used for classification. Model performance was evaluated based on precision and support, F1-score, accuracy and recall. Optimal parameters were selected using grid and random search. Result analysis PCA was superior to LDA. Hyperparameter tuning through grid search was superior to random search. Boosting methods yielded better results compared to bagging methods. The AdaBoost classifier with grid search and 10-fold cross validation achieved the highest accuracy of 94% using grid search.

Asmae et al. [38] employed ANN and k-NN for differentiating PD from healthy subjects. Dataset [22] comprised 31 subjects in total, 23 belonging to the PD category. They employed MATLAB tool for the purpose of classification. For ANN, 70% of the data was allocated for the training of the model, 5% for the purpose of validation, and the remaining 25% for testing. ANN reported an accuracy of 96.7%. For k-NN the data was partitioned in the ratio of 70% training data and 30% testing data. They implemented a 10-fold CV (cross-validation) strategy to mitigate the overfitting of the data. An accuracy of 79.31% was attained when k=1 and using cosine as a distance metric.

Z.K. Senhuk [39] proposed a model on how to go about the early detection of PD. They performed the RFE method as a feature selection (FS) task on a dataset [22]. They also considered ANN, CART, and support vector machines as the classifying techniques. They observed that the model improved after the feature selection. Without feature selection, the accuracies recorded were 85.23%, 79.98% and 80.25% for CART, SVM and ANN respectively. With feature selection, the accuracies increased to 90.76%, 91.54% and 93.84% for CART, ANN and SVM.

A new approach to identify the PD was introduced by Tuncer et al [40]. As the base method, the minimum average maximum tree, was integrated with singiuar valued decomposition (SVD) and, the relief feature selection method on the original dataset [29] to identify the top 50 features. The k-NN was employed as a classifying with a 10-fold CV. The highest classification accuracy recorded was 92.46%. Further processing of the individual results post classification increased the accuracy to 96.83%.

III. CONCLUSION

Research on neurodegenerative diseases is crucial, and finding methods to diagnose these diseases early is of utmost importance as it can prove vital to the affected individuals. In the past few years, new methods to analyze and interpret speech have shown great potential. This document details the various kinds of deep learning and machine learning (ML) methods to identify Parkinson's Disease (PD). Our objective is to demonstrate how PD can be diagnosed through the analysis of voice recordings. Given that the analysis of voice recordings is non-intrusive, it has been utilized across numerous fields, proving extremely valuable over the years in the classification and diagnosis of PD. In this document, we seek to evaluate the effectiveness of numerous classification models and their ability to monitor and diagnose PD, reducing the need for patients to make in-person visits to medical facilities.

Different classifiers were tested on various voice datasets, and it was observed that the random forest algorithm is the most successful machine learning algorithm, with an accuracy of over 99\%. The neural network classifier, which is among the deep learning methods, also achieved a commendable accuracy of 99.49\%. Therefore, artificial intelligence techniques have been extensively used for the preliminary diagnosis and detection of PD, and they have proven to be very effective and efficient.

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