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Complex System
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Parkinson’s Disease Detection [Report Writing]

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I'm putting together this project not just for academic purposes, but also to broaden my knowledge.

THANK YOU AGAIN TO EVERYONE WHO HAS HELPED ME.

Table of Contents

1. Introduction

Neurological problem Parkinson's disease mostly affects the brain's motor functions. Drugs may help Parkinson's disease sufferers feel better despite the fact that there is no cure. If the condition is discovered at an advanced stage, there is no treatment. Parkinson's disease, which alters the stride and posture and raises the risk of falling, is more common among the elderly.

Parkinson's disease does not yet have a definitive checkup analysis, and the incidence of carelessness is high, particularly when a non-specialist made the diagnosis: the probability of a mistaken result may be more than 20%. Key clinical aspects, such as shaking type, bradykinesia and stiffness, should be thoroughly evaluated to boost diagnosis accuracy, however physician subjectiveness may alter these findings (Cigdem & Demirel, 2018). It's exciting to see how medical decision support tools can improve objectivity and help with early diagnosis. Early detection of Parkinson's disease may lead to the development of individualized treatment options for those who are infected. Detection of Parkinson's disease relies heavily on the processing of speech, with longer vowel-like sounds and regular speech being used to make the diagnosis. Motion and gait may also be used to identify and monitor movement complaints in patients (Gil-Martin, et al., 2019). Computer-assisted diagnostics have gained a lot of attention for this reason. With the use of artificial intelligence (AI), healthcare providers may get better diagnostic tools and cut their costs at the same time.

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2. Aims

This report aims to know how Parkinson’s disease can be detected in early-stage as there is no cure in an advanced stage.

3. Objectives

i. To enhance the detection of Parkinson's disease in patients (PD).
ii. To provide a recommendation to treat patients accordingly to healthcare individuals.
iii. Various machine learning algorithms like CNN, SVMs, etc. will be viewed for detecting disease.
iv. Mobile and Desktop applications will be developed for detecting Parkinson’s disease.

4. Literature Review

4.1 Dynamically enhanced static handwriting representation for Parkinson’s disease detection

Parkinson's disease may be diagnosed by a person's handwriting, which is a kind of movement function of the brain that changes in writing from normal handwriting (PD). When an image is sent into a Convolutional Neural Network **(ConvNet/CNN),** the algorithm assigns weights and biases (learnable) to distinct parts of the image, and can distinguish between them.

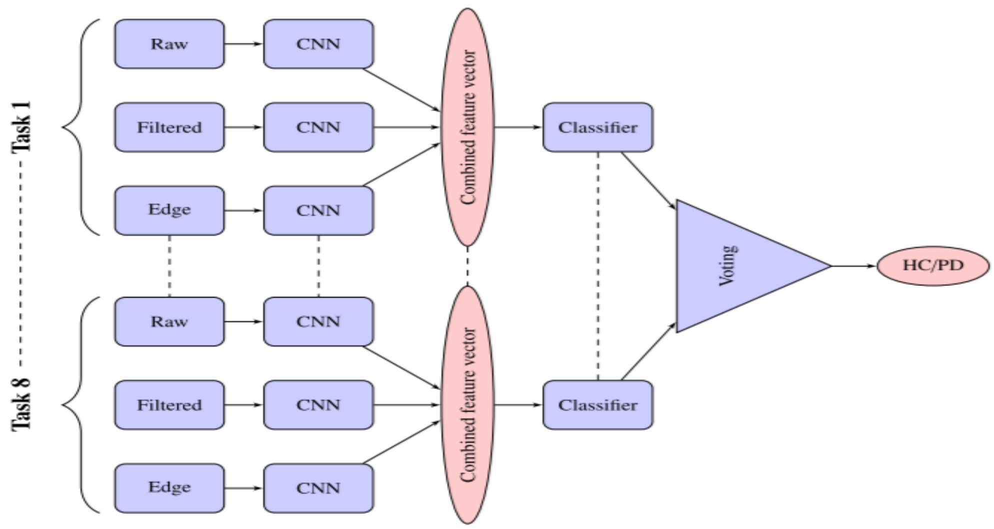

Figure 1 CNN classification workflow

One feature per task is created from the CNN features, which are then fed into a traditional machine learning algorithm for further processing. (Diaz, et al., 2019) analyzed data from both Parkinson's patients and healthy people in the PaHaW dataset using the VGG16 architecture (Diaz, et al., 2019). Using the ImageNet dataset, this is a well-known and commonly used CNN architecture. Convolutional base (up to block5 pool) was run on each input photo from the PaHaW dataset to accomplish transfer learning, removing the linked layers above the network that do categorization. The Keras-enabled VGG16 model was used in this study. It was first reduced to 150x150 pixels and then transformed into RGB before being used in the CNN model. Static, dynamic, and a variety of other handwriting traits are used to determine the accuracy of the feature extraction, dynamically enhanced static handwriting (velocity) (velocity and air). The dynamic handwriting function (i.e., on-line writing) has the highest accuracy of 88.67 percent (i.e. on-line writing). There have been significant findings in the area of on-line processing of preprocessed handwriting by Parkinson's sufferers (Diaz, et al., 2019).

4.2 Detecting Parkinson’s disease with sustained phonation and speech signals using machine learning techniques

As far as Lithuanian pronunciation is concerned, just one short sentence has to be considered in the context of phonation rather than speech. An **acoustic cardioid (AC)** and a **smartphone (SP)** were used to record the activity, allowing for an evaluation of the performance of different microphones. Five performance measures were used to evaluate categorization performance: **EER**, **AUC, Accuracy, Specificity, and Sensitivity**. Both phonation and speech tasks provided the data for this study, which was then divided into two distinct categories (Almeida, et al., 2019).

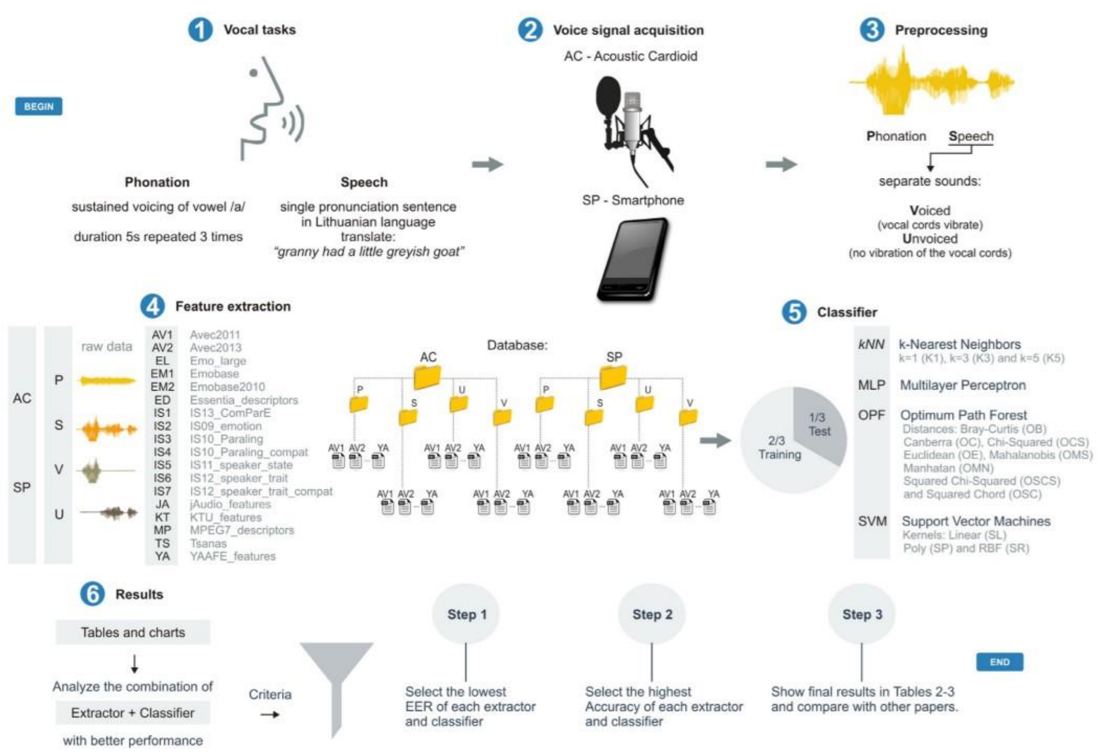

Fig. 2. Diagram of the proposed approachhas 6 steps: (1) The voice examination begins; (2) Voice signal acquisitions equipment; (3) Preprocessing audio signals; (4) Feature extraction with eighteen feature sets; (5) Hold-out validation to training the data set using four classifiers; and (6) Evaluation of the results and selection of the best combination of feature extractor and classifier.

Figure 2 working flow

(Almeida, et al., 2019) proposed technique is based on motor symptoms that are uniquely related to the vocal tract. There are two steps to this procedure shown in Fig. 2. Step 1: Two vocal responsibilities (see Fig. 2). Phonation and speech, or vowel voicing and phrase pronunciation, are examples of vocal tasks. The voice signal collecting device is the second step. So that they may evaluate the classifiers on AC and SP audio data. Audio signals from the previous phase are preprocessed in step 3. It is possible to create voiced and unvoiced files using the Praat Software Toolbox. The feature extraction process resulted in the creation of additional files for each feature set and modality. A total of 144 files were extracted. With the help of a hold-out technique, you may evaluate the database and four classifiers. Hyper-parameters for **k-Nearest Neighbour (kNN),** MLP, OPF, and **SVM** were improved using this method. One of the most fundamental Supervised Learning strategies is K-Nearest Neighbor. If a new case/data is similar to an existing one, the K-NN algorithm puts it in the most similar category. A neural network with nonlinear input-output mapping is known as a multilayer perceptron (MLP). In a multilayer perceptron, neurons are stacked on top of one another in hidden layers. It is possible to attain high identification rates and low processing costs by using the **Optimum-Path Forest (OPF) algorithm**. SVMs were faster at training than OPF, although OPF was slower in classification. Outlier detection and classification are two of the most common uses of SVMs. There are many advantages of using SVMs: When the number of dimensions exceeds the number of samples, it is useful in high-dimensional contexts.

The toolbox was used to train the three models, with the default hyper-parameters applied. The SVM classifier used three distinct kernels to classify the data.. Back-propagation was used to train the MLP, which includes hidden units ranging from 1 to 50. In order to train OPF, distance measurements were used. EER and Accuracy measures were used in step 6 to choose the best extractor and classifier combination. ROC and DET curves were used to determine AUC and EER (EER). Extraction and Classification Ratios (FNR and FPR) were balanced using the EER, which was used for two purposes: (FPR). A confusion matrix had been utilized to classify the data.

AC performance				SP performance			
		Predicted class				Predicted class	
		HC	PD			HC	PD
Actual class	HC	33.80	2.20	Actual class	HC	30.50	5.50
	PD	3.30	61.70		PD	1.70	64.30

Notes: PD - Parkinson's disease patient; HC - Healthy control subject.

Figure 3 confusion matrix of the classification result

There were a similar number of false positives and false negatives with the AC modality, which might be a plus for certain users. There were more false positives in SP mode. More healthy persons were misidentified for those with PD, according to this data. Phonation, rather than speech, was shown to be more successful in detecting disease. AUC (0.87), EER, and accuracy (94.55 percent) are all highest on the AC channel (19.01 percent). 19.01 percent of the population. Accuracy was 92%, AUC 0.92 and EER 14.15 while using the SP channel (Almeida, et al., 2019).

4.3 Parkinson's Disease Detection Based on Signal Processing Algorithms and Machine Learning

Sound, image, and mathematically generated data are all examples of signals that may be processed to communicate information. Applied signal processing here refers to the analysis of voice data from Parkinson's sufferers and healthy individuals. Signal processing techniques employed by (Rahman, et al., 2020) included the **Perceptual Linear Prediction (PLP)** and **Realitive spectral** PLP algorithms. Linear prediction analysis and spectral analysis are used in the perceptual linear prediction method (PLP). An audio spectrum may be calculated using components from the psychophysics of hearing using the PLP approach. RASTA and RASTA-PLP are not the same thing (Relative Spectral Transform - Perceptual Linear Prediction, a popular speech feature representation). RASTA utilizes a band-pass filter to smooth out short-term noise changes and remove any persistent offset produced by static spectral coloring in the speech channel. Short-term spectrum analysis of speech sounds is necessary to calculate PLP.

PLP Algorithm

This algorithm works by using spectral analysis, after that it pass the value into critical band spectrum resolution where Hynek Hermansky process is used to calculate the spectral resolution. The spectral resolution value is passed to equal loudness pre-emphasis where it uses intensity power law to find the loudness value. The obtained value is used in auto regressive modeling and liftering process.

Realitive Spectral PLP (RASTA-PLP)

The objective of this extension is to increase the durability and computing efficiency of the techniques utilized in traditional PLP.

The best accuracy obtained by using PLP based feature extraction was of 74 percent and with a classification accuracy of 68 percent acquired using an SVM model developed with an MLP kernel.

4.4 Parkinson's Disease Detection Using Ensemble Techniques and Genetic Algorithm

Ensemble algorithms, or "meta-algorithms," integrate different learning algorithms to create a predictive model to reduce variance (Bagging), bias (Boosting), or boosting predictive force (stack alias ensemble). A **genetic algorithm** is an exploratory technique that is capable of identifying the ideal solution to complicated problems in the majority of cases. The algorithm does this by storing a collection of trial solutions (commonly referred to as people) and forcing them to grow toward a suitable answer. Ensemble algorithm here combines two algorithms i.e. AdaBoost and Bagging algorithms (Fayyazifar & Samadiani, 2017).

<u>AdaBoost Algorithm</u>

AdaBoost, an acronym for "Adaptive Boosting," is a method for linearly combining weak algorithms to create a powerful classifier. It is a common binary classification technique based on the Boosting algorithm. The algorithm systematically instructs learners.

<u>Bagging Algorithms</u>

It (Baging) is an acronym for "bootstrap aggregation." It was the very first useful ensemble learning approach, as well as one of the more prevalent arching methods.

The datasets used by (Fayyazifar & Samadiani, 2017) were obtained from the UCI repository, which was created by Max Little of Oxford University. The first step is to apply a Genetic algorithm to minimize the feature vector and select the best collection of features. Data is then categorized into healthy and unhealthy categories using AdaBoost and Bagging ensemble techniques. For classification applications, the Genetic algorithm is an excellent optimization technique that may help you choose the optimal features. The Genetic algorithm was used to reduce the number of features in the feature vector. A total of 22 features are retrieved from each recording in the UCI Parkinson database. In the proposed strategy, each chromosome has 22 genes. Biological traits are encoded in a binary form in the DNA. They start with 20 chromosomes that were created at random. Fitness functions were utilized in this study based on the classification rate of AdaBoost as a Parkinson's disease classifier. In each generation, four of the best chromosomes, those with the greatest classification rate, are selected for production and alteration. The Bagging technique was then put to the test as a classifier to see whether it could accurately identify Parkinson's disease. There is a set number of iterations for AdaBoost and Bagging: 15 for AdaBoost and 5, respectively. Trial and error is used to determine the values of parameters.

There are categorization reasons, hence the Bagging strategy was selected by (Fayyazifar and Samadiani, 2017). A classification rate of 96.55 percent was achieved by the application of an algorithm that determined the optimal set of attributes. They then used an evolutionary algorithm to see whether it was possible to reduce the amount of characteristics that might be used in the categorization process. By executing the Genetic algorithm 15 times on six features, (Fayazifar & Samadiani, 2017) achieved a 96.55 percent classification accuracy.

4.5 Implementation of XGBoost for classification of Parkinson's disease

The researcher suggested Extreme Gradient Boosting **(XGBoost)** will be very helpful to determine PD. XGBoost is one of the implementations of gradient boosting (GB) approach, which is a classifier based on decision tree. It has been adopted due to its fast, efficiency, and its scalability. Gradient boost and XGBoost may be defined in the following fashion (Abdurrahman & Sintawati, 2020).

The dataset utilized by them came from the UCI machine learning library. Feature selection plays a vital part in identifying Parkinson’s disease (PD) where to plot the feature importance, the XGBoost library keeps the built-in function. XGBoost feature importance was used to filter the efficiency of the features to increase the classification model's accuracy.

Features	*Variables*	Data type
Jitter	X1	Nominal
Shimmer	X2	Nominal
Fundamental Frequency Parameters	X3	Nominal
Harmonicity Parameters	X4	Nominal
Recurrence Period Density Entropy (RPDE)	X5	Nominal
Detrended Fluctuation Analysis (DFA)	X6	Nominal
Pitch Period Entropy (PPE)	X7	Nominal
Decision Class (Parkinson)	Y	Ratio

Figure 4 Properties of feature-based

Data from the University of California, Irvine (UCI) does not have a missing value. So, the classification technique is used to determine whether a patient has Parkinson's disease or is otherwise healthy. The categorization model utilizes a machine learning approach called the process. Modeling was carried out using the XGBoost technique. As part of the dataset, 0.333% of the total data was used for testing and the rest was used for training. First, the dataset is classified by utilizing the XGBoost technique, which includes all baseline features and has an accuracy score of 84.80%. Then, features are selected by mapping feature importance to the XGBoost feature importance score.

After carrying out the findings of attributes, the accuracy obtained was 85.60 percent . after having accuracy less than 90 percent, they again performed the process by excluding the value of F-score which is less than 20 and the accuracy they obtained was 84.40 percent. So, they finally go further process with the previously obtained accuracy of 85.60 percent.

5. Analysis of Finding

Different researchers used different machine learning models and algorithms to detect Parkinson’s disease(PD) at an early stage. They used different datasets to calculate the accuracy of the detection of PD. Some of the findings are shown below in the table:

S.N.	ML models and Algorithms	Dataset	Accuracy(in %)
1	CNN	PaHaW(Handwriting dataset)	88.67
2	kNN,MLP, OPF AND SVM	Phonation and Speech	Ac channel – 94.55 SP channel – 92.94
3	PLP, ReAlitive SpecTrAl PLP (RASTA-PLP)	Speech	74
4	Ensemble(AdaBoost and Bagging) and Genetic algorithm	UCI machine learning repository	96.55
5	XGBoost	UCI machine learning repository	85.60

In the above table, we can see that various machine learning algorithms were used with the result of different accuracy. The highest accuracy is 96.55 percent which will be the very best method to detect disease but the process of using ensemble and the genetic algorithm will be time-consuming as they have to iterate through approx. 20 to 30 times only of genetic algorithm. Using the same datasets, the XGBoost algorithm gets an accuracy of 85.60 percent but it works faster as suggested by (Abdurrahman & Sintawati, 2020). There is a huge difference in the accuracy of speech datasets. Using kNN, MLP, OPF, AND SVM, the accuracy is approx.. 92.94 percent but with the PLP, ReAlitive SpecTrAl PLP (RASTA-PLP), the accuracy is just only 74 percent which is very less accurate than that of other approaches.

6. Conclusion

Hence, Parkinson’s disease can be detected in an early stage with the help of machine learning approaches. In the early stage of PD, symptoms of speech blurring and handshaking will be seen. While performing the various research, the machine learning approaches using handwriting datasets and speech datasets had a better accuracy of 88.67 percent and 94.95 percent respectively than that of other approaches. A better system will be developed to detect Parkinson’s disease with the help of kNN, MLP, OPF, AND SVM or CNN machine learning approaches.

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