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Privacy-Preserving Deep Speaker Separation for Smartphone-Based Passive Speech Assessment for Parkinson Diseases

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ABSTRACT: Smartphones is used to test and controlling and supervising' speech difficulties caused by illnesses like Parkinson's disease in a proportionate manner. Parkinson's disease (PD) is caused by a lack of dopamine, a chemical that governs many bodily functions. Researchers have discovered that voice loss is a sign of Parkinson's disease. Machine learning (ML) has recently aided in the resolution of issues such as pattern recognition, NLP and voice recognition. The purpose of this work is to investigate the impact of feature type selection, namely MFCC and TQWT, on the effectiveness of a voice-based PD detection system, as well as the usage of an ensemble learning-based classifier for this job. As a result, different machine learning models, such asLogistic Regression, Naive Bayes, KNN, Random Forest, Decision Tree, SVM, MLP, and modified Recurrent Neural Network (mRNN), were used and examined in this study for PD identification. Minimum-Redundancy and Maximum-Relevance (mRMR) and Heuristic Algorithms Elimination (RFE) approaches were also used to choose features. When both MFCC and TQWT features were picked, the MRNN with mRMR feature selection surpassed all other models with a high accuracy of 95.39 percent and precision, recall, and F1 measure of 0.95 each. The findings significantly support the adoption of the mRNNmodel in conjunction with the mRMR subset of features approach for speech sample-based PD identification.

KEYWORDS: Monitoring System, Performance evaluation, Machine learning, heart diseases

I. INTRODUCTION

Parkinson's disease is a neurodegenerative illness caused by the loss of the neurotransmitter dopamine. The elderly are more likely to develop Parkinson's disease, which causes changes in gait and posture that may increase the risk of falling and create mobility issues. As a consequence, it has an impact on daily activities and affects the quality of life for patients and their families. Parkinson's disease mostly affects the motor system. This movement condition manifests itself in the inability to move freely, slow movement, increased muscular tonus, and shaking movement in the resting position. A lack of facial expression, trouble with coordination, and noticeable variations in speech and voice are among the other features. People with PD may lose their sense of smell and have sleep difficulties during the rapid eye movement sleep phase. Parkinson's disease is expected to afflict around 1% of the population over the age of 60. In the vast majority of instances, the aetiology of Parkinson's disease is unclear. Pathological alterations in dopaminergic neurons and the resulting neurochemical dysfunction have been revealed to be the most conspicuous features of this illness. The bulk of dopamine-producing neurons in the brainstem comprise the substantia nigra, a black material. This anatomical region is linked to other deep brain areas and is involved in the creation of regular bodily movement. Lack of dopamine production in the dopaminergic neurons of the substantia nigra limits range of motion and impacts voluntary movement. Parkinson's disease has no cure at the moment. The illness progresses at different speeds and on different paths. Parkinson's disease symptoms may be treated with a variety of medications. Natural speech analysis and support vector machines were the models employed in [1] to make a diagnosis of Parkinson's disease using a database of PD cases.

This paper's structure is as follows: Section 2 substantiates the evaluation of previously conducted research on PD detection. The suggested mechanism for PD detection is presented in Section 3. The categorization findings are analyzed and discussed in Section 4. Section 5 brings the paper to a close.

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II. LITERATURE SURVEY

Because the convolutional neural network technique is designed to uncover meaningful features based on raw training data, we kept the preprocessing following the time–frequency conversion minimal and deleted the stages for feature development. The preprocessing is maintained the same to compare standard machine learning techniques to neural network topologies. All classifiers employ the same random separation in training and test sets. However, it should be noted that if more effort is put into feature extraction and preprocessing procedures, the results will be equivalent to those shown in [1].
Close to the wall or near the corner of the wall is the optimal location for the sensing device to acquire a strong back scattered signal. The amplitude of the periodical frequency modulation around the central carrier frequency shows that there are adequate reflections back to the device from both locations. The primary reason for this is because the huge ground plane reflects the echo back to the device above it. However, the positioning closest to the corner of the wall offers the greatest back reflection. This is due to the corner of the wall's Multi-path reflection additive. Corner reflection has previously been shown to be effective in radar applications [2].
Back reflection of movements made on a mobile device placed within a trouser pocket was shown to be fairly feeble in prior research [3]. Both transmission and reception of the signal are impaired. As a result, clothing or towels should not be placed over the measurement instrument. However, in order to have adequate signal back propagation, the detecting device's volume must be turned all the way up. When the speaker and microphone are in the same room, the recording might have unanticipated amplitude changes, which can pose problems for this processing procedure. Furthermore, utilising the phone's speakers at full volume increases the amount of eigenfrequency stimulation, which may fall outside of the human hearing range, causing the user to be disturbed.

The SVM calculates the shortest distance between hyperplane borders. The margin is the distance between the two borders. The support vector machine, unlike logistic regression for binary classification, does not offer probabilities and merely produces a class identity. Non-linear data may also be classified using SVM. This is accomplished by a technique known as kernel trick. The SVM attempts to linearly separate the data by transforming non-linear data from a lower dimension to a higher one. SVM is a binary classification scheme in general, but by applying the one-versus-rest or one-versus-one approach, it may be expanded to a multi-classes algorithm. SVM theory may be found in a variety of textbooks [4].

One completely linked layer is employed at the upper network layer to connect all of the learnt characteristics. The last layer delivers the final class classification forecast. The softmax layer is the second dense layer, and it outputs the probabilities for each class. RMSprop as the optimizer and ReLu Layer as the activation layer are used to learn and update the weights in each individual layer. Hinton et al. [5] proposed the equation for the ReLu activation layer. The gradient descent algorithm only learns the weight at the activation range in this scenario. Hinton et al. [6] were also the first to introduce the RMSProp equation. A running average of the magnitudes of recent gradients for that weight is divided to update the learning rate for that weight. The benefit is that it eliminates the issue of overshooting the global optimum and allows the network to swiftly converge to it.

All of the HR monitoring systems mentioned above are contract-based, requiring the user to maintain their fingertip in close proximity to the smartphone camera lens with enough force. Any change in finger position or lighting situation might lead to an incorrect HR estimation [7]. The PPG signal produced from the video of the face is used by contactless monitoring devices to assess HR. Reference [8] described a non-contact heart pulse monitoring programme called FaceBeat. The software used an algorithm that was comparable to the first-of-its-kind video-based HR monitoring system described in Reference [46], which used a laptop's camera to capture video. FaceBeat extracts cardiac pulse and calculates HR from a video of a user's face taken with the smartphone's front camera. The camera sensor's photodetector array detects changes in reflected light from a particular area of interest (ROI) in the face when blood volume in the facial blood vessels changes. The authors used the recorded video's green channel data, which, according to References [9], is best for measuring HR, especially in the presence of motion artefacts. To extract HR and HRV, the authors employed independent component analysis (ICA) to eliminate noise and motion artefacts from the ROI video data and frequency domain analysis on both the raw and decomposed signals. In comparison to the reference ECG signal produced using a commercial ECG monitor, the HR thus measured had a maximum average inaccuracy of 1.5 percent. However, the application's complicated computing process increases CPU load and computation time, resulting in higher power consumption and shorter battery life.

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Rather of using the traditional way of estimating HR by detecting variations in the hue of reflected light from the face, researchers in Reference [10] presented a method that measures both HR and RR by detecting variations in the hue of reflected light from the face. A video of the subject's face was captured for 20 seconds. To find the major frequencies in the time-varying variations of the average Hue, just the frontal area of the face was studied in the frequency domain. The authors claimed to have achieved very precise HR and RR readings, with the green channel PPG having a greater correlation to conventional devices. However, if the forehead skin is covered by anything, such as hair, a headband, or a hat, or if it includes scar tissue, this method may not work. Although face-based contactless HR monitoring is a more comfortable option than contact-based devices, its effectiveness may be affected by changes in lighting, skin colour, facial air, scars, and facial movement.

III. PROPOSED METHODOLOGY

Figure 1 shows the process for developing a model to predict Parkinson's disease at an early stage employing machine learning techniques. It comprises of the stages listed below.

A. Architecture

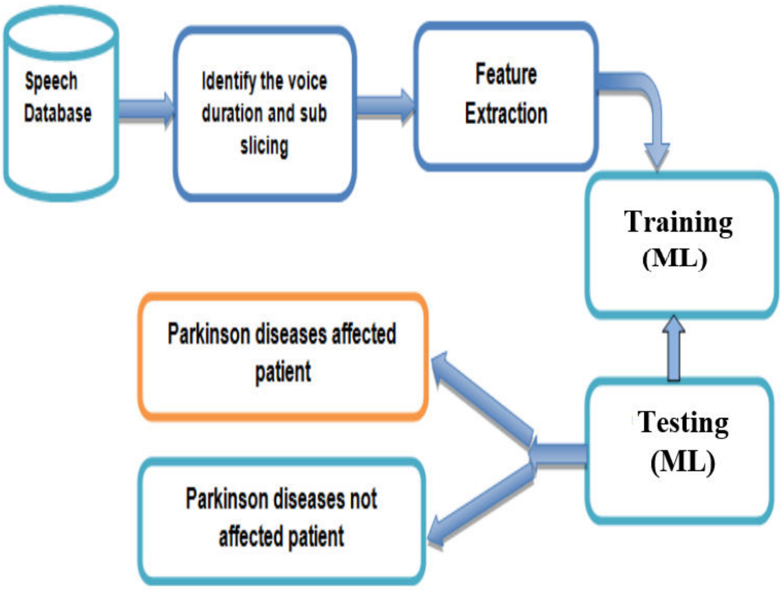

Figure1: System Architecture

Individual pieces of the conceptual methodology have been described in depth below. This stage is made up of two separate processes: data normalization and feature extraction methods or selection, both of which are described below.

Data Normalization :

Data normalization is a data processing technique that is often used with most machine learning algorithms when dealing with datasets. It modifies the numeric values of sections without affecting the data. It's needed to rescale the values of a certain feature within a given range. Because the feature values in the chosen dataset were of varied ranges, they were standardized using the Min-Max normalization approach between the ranges (0, 1) in this study. The following is a description of this normalization: $MinMax(X) = \frac{x_i - X_{min}}{X_{\max} - X_{min}}$

where X is a specific characteristic represented by a dataset column, xi is a value for this column, and I is the number of items in the column The column's lowest and maximum values are denoted by the letters Xmin and Xmax. Following the normalisation of characteristics, two feature selection strategies, RFE and mRMR, are used in our suggested study. The mRMR [25] feature selection algorithm ranks features based on their redundancy with other qualities and relevance to the class label. The RFE [6] [7] [8] iteratively eliminates features and builds a model using the remaining characteristics before evaluating the model's performance. The chosen characteristics were trained using several techniques, which improved the efficiency of our suggested model.

The model is implemented once the features are chosen, and the output is in the form of probability or a class. The next stage is to use the test dataset to determine how productive the model is based on certain metrics. To evaluate the classification performance, we employed several measures such as accuracy, recall, precision, F-1 score, and AUC-ROC curve. The criteria used to assess the classification model are critical because they determine how performance is evaluated and compared.

B. Algorithms

Algorithm 1: Proposed modified Deep Neural Network Algorithm (mRNN)
Input: Train_Feature set [], // Set of training dataset
Test_Feature set [] //Set of test dataset
Threshold denominator Th
Collection List cL
Output: Generate class lable for all test instances based on classification results.
Step 1: Read all attributes from Testing dataset using the below function

$$\text{Test\_Feature} = \sum_{j=1}^{n} (\text{T[j]})$$

Step 2: Read all attributes from the training dataset using the below function

$$\text{Train\_Feature} = \sum_{k=1}^{m} (\text{T[k]})$$

Step 3: Read total attributes from train instnaces using below function
Step 4: Calculate the similarity index and generate weight for both feature set

$$Weight = classifyInstance(\text{Train\_Feature}, \text{Test\_Feature})$$

Step 5: Verify with Th

optimized_Instance_result = Weight >Th ?1 : 0;

Add each optimized_instance to cL, when instances = null
Step 6: Return cL

C. Objectives

- To design and developed Machine learning classification-based health care system for Parkinson disease prediction.
- To design and develop a various feature extraction and selection techniques for module building.
- To design and implement a various machine learning classificationalgorithm for prediction of Parkinson Disease.
- To explore and validate the proposed system results with various existing systems and show the effectiveness of system

D. Problem Statement

The issue is that MFCC characteristics are susceptible to background noise and cross-talk (overlapped speech). When cellphones are used for passive evaluation in real situations, cross-talk, which happens when a smartphone collects background speech that does not belong to its user, is a typical issue.

E. Mathematical Model

Many users can obtain one result or multiple results.
Set Theory:
S= {s, e, X, Y}
Where
s = Start sensor and application of the program.

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Log in user.
Get the data from sensors or synthetic data
e = End of the program.
Display the captured data on the monitor screen.
Log out the user.
X = Input of the program.
Input should be synthetic data set.
Y = Output of the program.
Finally, this display the captured data on the monitor screen.
Let S be the Set of System.
S= {U, I, A, C, R}
Where U, I, A, M, R are the elements of the set.
U=User
I=Input synthetic data.
A=Application monitor patient data
C=Classification (Training, Testing) data set
R=Result.
Failures:
Hardware failure.
Software failure.
Success:
Search the required information from available in **Datasets or Database**.
User gets result very fast according to their needs

IV. RESULT AND DISCUSSIONS

It makes sense to correlate quantitative assessment and clinical scores and could potentially address many challenges in decision-making. The generated training repository was applied with various machine learning models to establish patterns of common, questionable and dangerous activities. To test and rate the machine learning strategies, the various cross-validation model was employed using the behavior classification, training-database. Figure 2 below displays the 10-fold classification technique used on all parameters and explains all implementations' consistency.

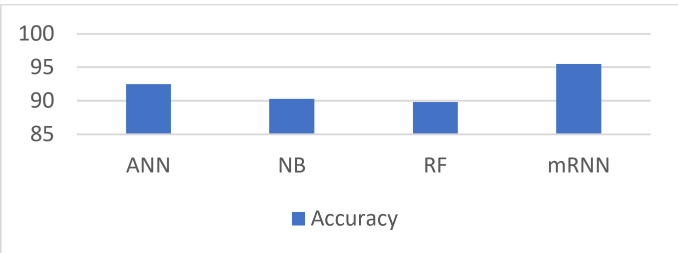

Figure 2: Accuracy evaluation of various ML and mRNN classification

Figure 2 shows the overall accuracy of all approaches, including the suggested mRNN. Its accuracy percentage is 95.50%. The minimal accuracy of Linear Regression RF is 89.8%, which is greater than other approaches.

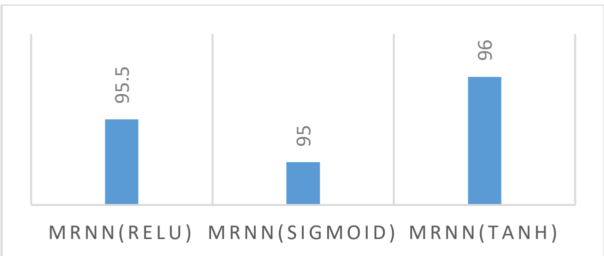

Figure 3: mRNN classification accuracy with various activation fucntion

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The above Figure 3 describes experimental analysis with three different functions of RNN. The TanH provides highest accuracy as 96.00% which is highest than other activation functions.

The above figure 2 and 3 improves the importance of different experimental research focusing on various statistical tests with numerous distinct algorithms such as NB, RF and ANN. For data management, the mRNN classification algorithm was used during the classifier. The neural network was shown and debated for each model. Both uncertainty metrics show the system accuracy of properly classifying, wrongly classifying, recession, and device recall

V. CONCLUSIONS

The Parkinson's disease research field is now very important, and early identification may help patients live a better life. Speech analysis has yielded considerable results as a consequence of recent improvements in methodology. In our research, we used a machine learning strategy to solve the challenge of detecting Parkinson's disease, and we used many kinds of machine learning models to do so. The major goal of this project is to demonstrate how speech signals may be used to diagnose Parkinson's disease. Speech processing has long been thought to have enormous promise in the identification of Parkinson's disease since voice measures are non-invasive. The goal of this project is to evaluate and compare the performance of different categorization methods. On a speech dataset, the various classifiers were applied, and various assessment criteria were compared using visualisation and statistical analysis. In machine learning algorithms, it was discovered that the mRNN beats all other classifiers. The accuracy of the RFE feature selection approach was 95.50 percent, while the accuracy of the mRMR feature selection technique was 95.80 percent on all feature subsets, which is greater than all state-of-the-art techniques. The following may be suggested based on the findings.

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