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A novel framework for the diagnosis of Parkinson's disease using transfer learning with RESNET50 and SVM classifier

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ABSTRACT

Most Parkinson's patients exhibit voice disorders in the early phases of the condition. Recent study on Parkinson's disease (PD) has concentrated on identifying speech problems from pronunciation of vowels with people affected by this disease. Proposed algorithm offers analysis of time-frequency images using transfer learning methods with support vector machine (SVM) for classification of PD affected with healthy controls using residual network 50. PD morphology is preserved in 2D time-frequency graphs that were helpful in implementing the proposed approach. The technique employs a hybrid HT/Wigner-Ville distribution to convert one-dimensional (1D) PD soundtracks to two-dimensional (2D) time-frequency (TF) graphs. After implementation of the proposed approach, classification of healthy and unhealthy controls is done using a pre-trained ResNet50 and the result is further improved through transfer learning. The features are extracted by passing preprocessed 2D time-frequency diagrams through ResNet50's FC1000 layer and trained using a binary nonlinear SVM classifier. The training process with 5-fold cross-validation (CV) got accuracy of 95.07% and in testing; it reached 92.13%, attaining better results.

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1. INTRODUCTION

One percent of those over the age of 60 are affected with Parkinson's disease (PD) [1]. American and European epidemiological research has shown that males are observed to be affected with PD more likely than women. PD progressively impairs mobility, which has an impact on daily living. In the central nervous system of the midbrain, also referred as substantia nigra, dopamine loss causes progression of disease [2]. 90% of people with Parkinson's exhibit vocal disorders at early stages and the speech issues were the subject of a recent PD telemedicine study [3]. This research used voice signal processing to assess PD. Systems for trustworthy decision assistance were constructed using the generated characteristics. PD results in bradykinesia, postural instability, stiffness, and resting tremors [4].

A publicly available dataset comprising 195 voice recordings from 23 patients and eight non-PD is used in several studies that compare people with and without PD [5]. Voice recordings from 20 persons with PD and 20 participants without it makeup a PD dataset [6]. The primary vocal frequency and amplitude characteristics are all included in each voice recording in all datasets.

People affected with PD is observed to have various symptoms while the clinical analysis done by clinicians, but it has become a complex procedure to assess the patient at early stages of the disease. Though there are many studies conducted and various machine learning models developed to support the decison by clinicians, most of those could not perform well. So, to aid clinicians for diagnosis of disease at early stage, the voice signals are taken from two categories of people, those with disease and without disesase. Since the machine learning models could not suffice the required support for classifying the people, so deep learning and transfer learning models with convolutional neural network (CNN) are proposed through this research. Also, the input for the research is generated as spectrograms for 1D audio signals. These 2D images are fed to the network and when tested achieved better results than existing techniques.

Rest of the paper is arranged in the order as follows. “Related Work” Section discusses about the existing and past research done by various authors. “Method” section discusses the proposed method through transfer learning and classification model along with insights of one-dimensional (1D) to two-dimensional (2D) transformation techniques. The “Results and Discussion” part discusses the results achieved and comparison of metrics with other methods, performance of classification and findings. Finally, “Conclusion” section makes recommendations for further research.

2. RELATED WORK

Research on PD speech analysis also involves collection of voice data procedures. Because it is frequent work, sustained vowel phonation is common. In other studies, prosody is studied using continuous voice recordings of sentences, text reading, and spontaneous speech. Few studies have looked at single-word creation. People living with Parkinson’s were the subject of early research [7]. Parkinson’s patients were divided into groups by using a support vector machine (SVM) with a Gaussian kernel by researchers. Both individual attribute sets and the sum of all coefficients were compared. Word and vowel accuracy were 92% and 79%, respectively, when all utterances and features were merged. Despite having successful results, the method needed preprocessing.

The speaking challenge of pronouncing words with the speakers from Czech, German, and Spanish, are represented in the database (20 speakers are PD affected, 16 are healthy controls) [8]. Speakers of healthy controls and PD were automatically categorized using several languages and feature sets. Four classes were used to model each corpus to detect language impairment. The authors stated that the latter approach was robust and had a classification accuracy of 85% and 95% when using a radial basis SVM. On a single dataset, none investigated model generalization. Because the test models were tuned, the results were too optimistic.

Karan *et al.* [9] suggested using hilbert spectrum features to explain non-linearity of speech signals. When dealing with individual syllables, usage of suggested coefficients outperformed conventional acoustic characteristics. They have omitted to provide the results of the combined characteristics. Twenty Parkinson’s sufferers and twenty healthy controls were employed [10].

Each patient reportedly produced six phonations, according to little [5]. The phonations were picked up by an industrial acoustics company’s soundproof audiology booth. In a digital voice lab, human sound waves were captured. They examined entropy as well as conventional and nonstandard metrics after recording phonations. A kernel based SVM classifier used to categorize people living with Parkinson’s and healthy people. Das used decision trees, regression, DM neural, and neural networks to categorize features [11].

Hoq *et al.* [12] proposed an SVM model to select PD features. Vocal features were then extracted and arranged with help of a method known as the greatest relevance lowest redundancy (mRMR). The test performed on the UCI voice dataset yielded an accuracy of 81.53% using the leave-one-individual-out technique and 92.75% utilizing the resampling method.

This study suggests a strategy to perform analysis of single words pronounced by the people on various signal processing and pattern identification techniques. Pre-processing comes first, then a conversion of 1D to 2D is done and binary classification. To show additional data such as time, frequency, and energy, the PD vocal features are transformed into 2D time-frequency (TF) diagrams. The method uses the HT to convert the original signal into analytical signals first, and then uses the conventional wigner-ville distribution (WVD) to analyze time and frequency to produce the necessary time-frequency diagrams.

3. METHOD

3.1. Method outline

In order to determine time, frequency, and energy information from each of the signal’s, the 1D voice signals are converted into 2D time-frequency diagrams using the HT-WVD approach. Figure 1 displays the architecture of the proposed technique. The dataset that is generated is split into a training set (70%), validation set (10%), and test set (20%). A random shuffling of samples happens for each of these splits.

The dataset of the validation set is utilized using a 5-fold CV approach for verifying the effectiveness of the trained transfer learning models. The value of learning rate is set to be 0.001. Multiple transfer learning models are trained using the training data. The images generated as part of 1D to 2D conversion are classified using transfer learning using the ResNet-50. The test data shows the classification results with the best learning model.

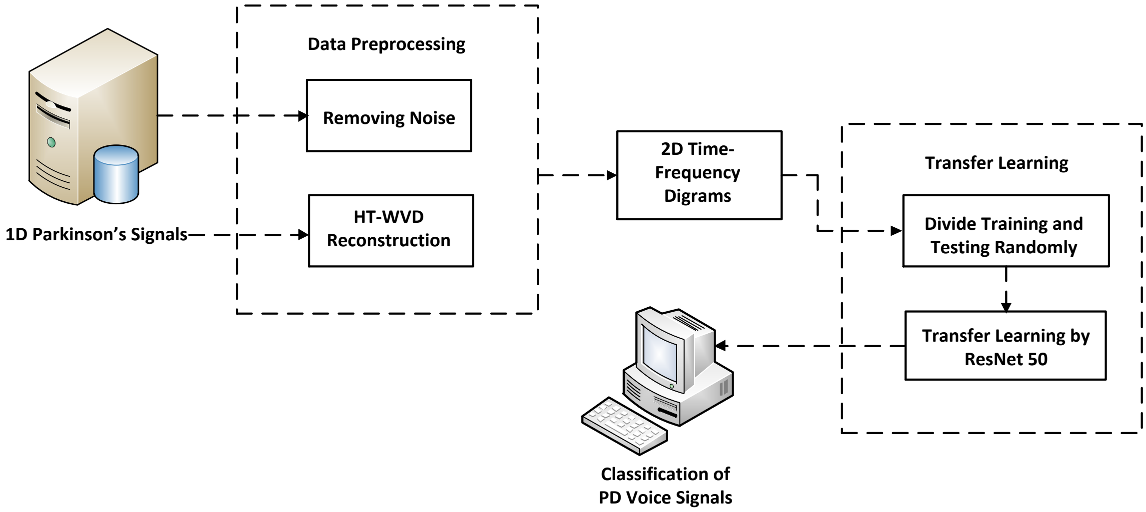

Figure 1. Architecure of the proposed method

3.2. Pre-processing of dataset
3.2.1. Noise removal process

The voice data collection includes well-known BW and power line noise at 50/60 Hz. In order to assure accuracy, noise should be removed from the recordings. This study initially removed BW from PD recordings using a median filter method before removing power line noise using a wavelet transform method. The median filtering method was used to obtain the baseline curves from the PD recordings. To create the new PD recordings (without BW), one must first apply a median filtering technique [13]. The wavelet transform was used in this study to reduce extra noise. The three-level wavelet decomposition is made using the Daubechies db5 wavelet.

3.2.2. Time and frequency analysis

PD speech signals cannot determine the relationship among space, frequency, time, and energy. In order to determine the count of frequency components that were identified in the voice signals, time-frequency analysis methods may transform a 1D signal into a 2D density function. The signal analysis uses temporal frequency techniques like the WVD and HT [14], [15]. Normalization of 1D signals is not a mandatory step here as the dimensional difference of them is not affected when converted to 2D time-frequency diagrams [16]. Figure 2 displays the flowchart for analysis of the time and frequency.

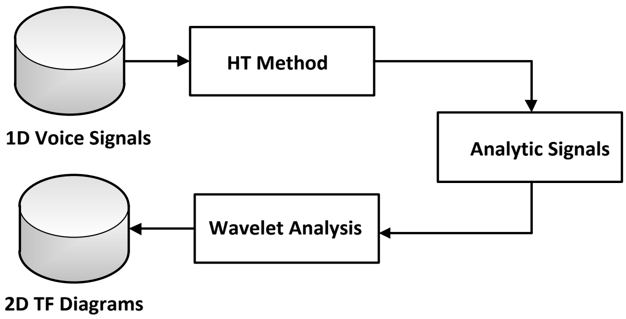

Figure 2. Process of 1D to 2D TF diagrams

Figure 3 represent the 2D time-frequency audio signals of the Parkinson's when pronounced the vowel 'A' and Figure 4 represent the 2D time-frequency audio signals of the healthy person when pronounced vowel 'I'. Likewise, all audio signals for both PD and healthy control signals are generated with the signals of time-domain, spectrum, and spectrogram. The input data for the proposed method is the set of 2D spectrograms that were generated from the 1D audio signas, which are the vocal recordings of the people from both categories, those affected with PD and healthy controls. As 1D signal cannot be used in deep learning techniques, this transformation from 1D to 2D is done. The frequeny Vs time digrams of Figures 3 and 4 are the input images that are fed to the network for experimental set-up. The 2D TF diagrams are also generated by PD affected when pronounced 'I'and healthy control when pronounced phonation 'A'.

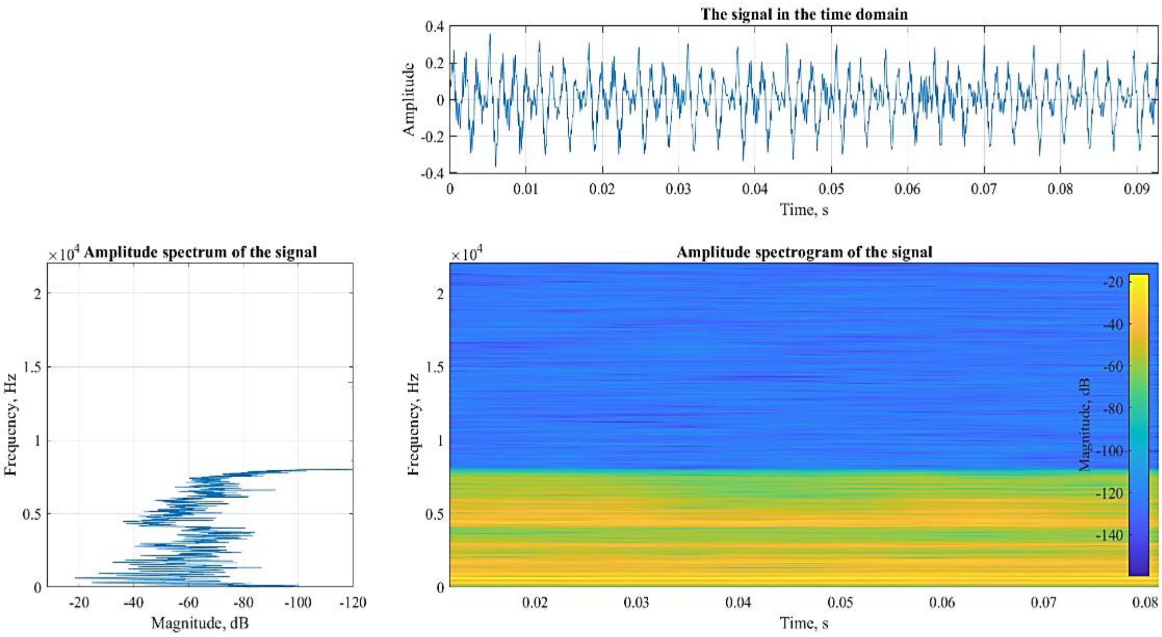

Figure 3. 2D TF diagrams generated by PD affected when pronounced 'A'

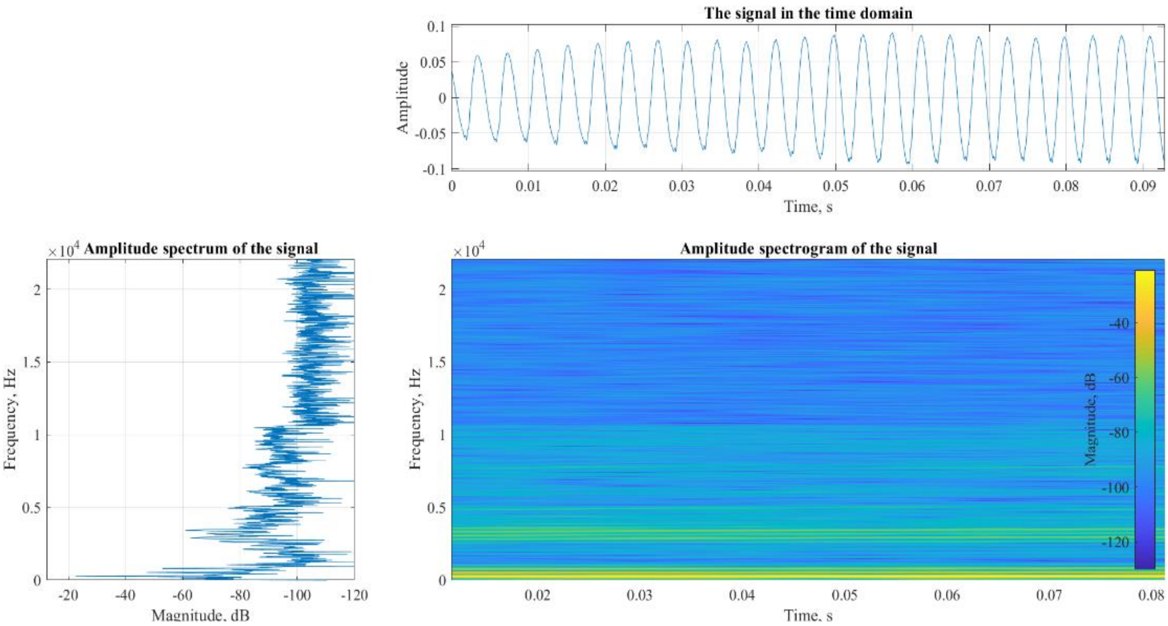

Figure 4. 2D TF diagrams generated by healthy control when pronounced phonation 'I'

3.3. Concept of transfer learning

In Figure 5, feature extraction is shown. A dimensionality reduction called feature extraction uses many pixels to effectively represent exciting aspects of a picture, such as a person's vocal characteristics [17], [18]. The most recent FC1000 layer's pre-trained ResNet50 network produces 2,048 features per image. The recommended classification flow is shown in Figure 6. ResNet50 network and multiclass nonlinear SVM [19] are used during training.

Compared to other classification methods, SVM is a supervised learning technique that linearly separates the categories of data with help of hyperplane thereby making the test samples more predictable. Here in the suggested methodology SVM is configured with radial basis function (RBF) kernel, which is a multi-class non-linear kernel. Once all the features passed to SVM, the knowledge base is prepared which is used in testing phase.

Finding connections between samples with label information and new sample is a critical component of transfer learning [20]. The transfer of information across the source and target domains is the primary goal of this learning process. For this purpose, the pre-trained ResNet50 is used which passes images to the fully-connected (FC) layer where the extaction of featurs are done here, later passed to SVM.

Figure 5. Process of feature extraction

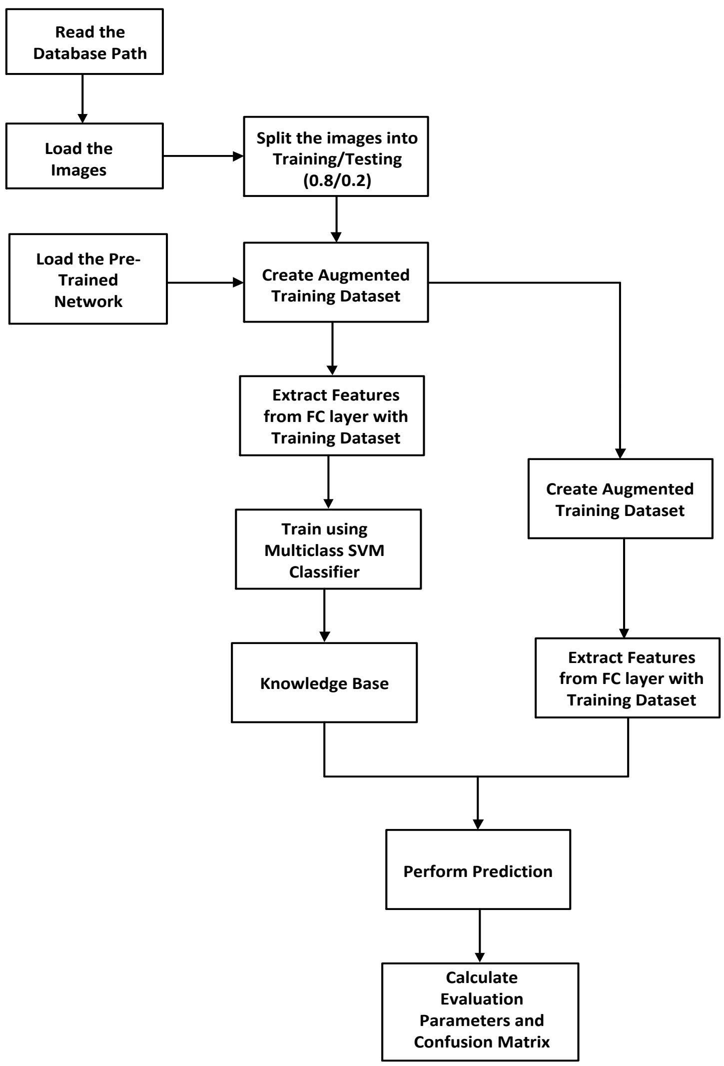

Figure 6. Flowchart for classification

3.3.1. ResNet50 network

The 49 convolution layers for training in the ResNet50 Network are divided into three and one fully connected layers. Training images are sent to the network already processed. Learning via transfer is better. The pre-trained network's FC1000 layer features are utilized for nonlinear SVM classification with the RBF kernel [21]. ResNet50 details are shown in Table 1. Convolution, rectified linear units (ReLu), and SoftMax are shown in (1)-(3).

$$(f * g)(t) = \int (r)(t - r)dr \quad (1)$$

$$f(x) = max\,(0, x) \quad (2)$$

$$z(i) = ezi/\sum_{i=1}^{k}.ezi \quad (3)$$

Table 1. Details of ResNet50 architecture

Name of layer	Size of output	Layers
Input	224x224	7x7, 64, stride 2
Conv1	112x112	7x7, 64, stride 2
Conv2	56x56	[1x1, 64 3x3, 64 1x1, 256]x3
Conv3	28 x 28	[1x1, 128 3x3, 128 1x1, 512]x4
Conv4	14 x 14	[1x1, 256 3x3, 256 1x1, 1024]x6
Conv5	7 x 7	[1x1, 512 3x3, 512
	1x1	1x1, 2048]x3
		Average pool
		1000-d fully connected softmax

3.3.2. Binary classifier-support vector machine

A famous supervised classification and regression technique is SVM. It separates target classes that are n-dimensional or multidimensional. The fundamental objective of SVM is to build the best decision boundary (with the highest margin) to classify new data points. In n-dimensional space, there may be several lines or decision boundaries. We still choose the most straightforward decision boundary for data categorization, hyper plane SVM. Dataset properties determine hyper plane dimensions [22]. Hyper planes that maximize the margin are produced. This margin constraints datapoint distance. In order to split n-dimensional data points, locate a hyper plane. The kernel computes the x-n and x-m distances. Scores are more excellent for data points that are more closely spaced. Figure 7 shows the classification process of an SVM.

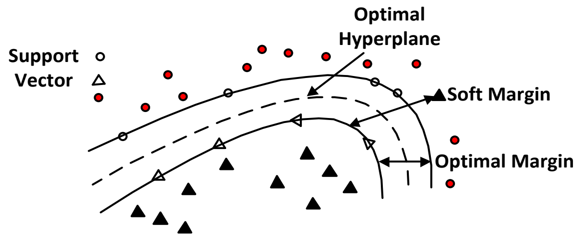

Figure 7. Non-linear SVM

Similar to the K-nearest neighborhood (K-NN) algorithm, RBF kernel is used. Keeping support vectors during training helps K-NN and gets around the space complexity issue. Several kernel-based machine-learning techniques, like SVM classification, use RBF kernels. RBF kernel math [23] is shown in (4). The information base for training is expanded. Test data of images are used to assess the categorization performance metrics. Preprocessing, feature extraction, and knowledge base processes are applied to the testing data:

$$K(X_i, X_j) = \exp\left(-\left(\frac{\|X_i - X_j\|^2}{2\sigma^2}\right)\right) \text{for } \sigma > 0 \quad (4)$$

where X_i, X_j are called feature vectors.
'K' is kernel and 'σ' represents kernel spread.

3.4. Dataset description

Voice recordings of 20 people are collected for this study, 10 have Parkinson's and 10 are healthy controls. 188 patients with the condition, ranging in age from 33 to 87, provided the data for the study. 10 healthy individuals between the ages of 41 and 82 make up the control group, with 5 men and 5 women. The microphone was set to 44.1 kHz for the collection of data. Every participant's phonation of the vowels /a/ and /i/ was recorded with doctor's examination. The example 2D TF diagrams utilized in this study are shown in Figure 8.

PD_09_a

PD_09_i

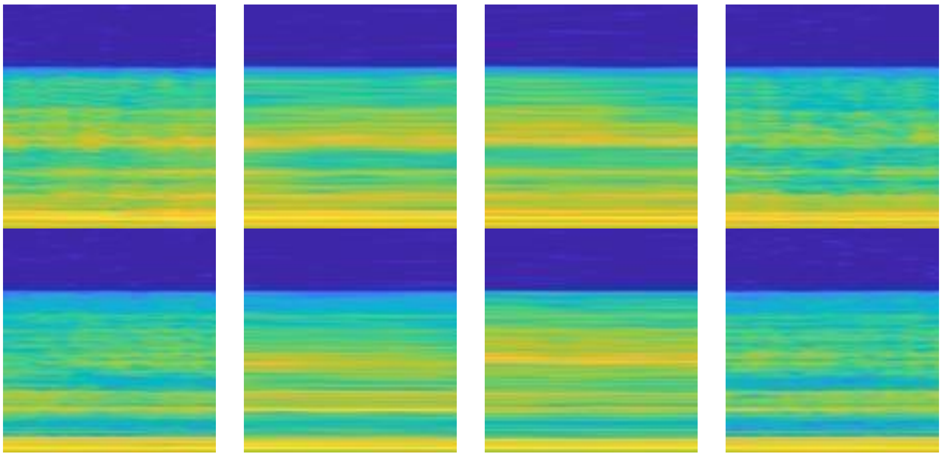

Figure 8. 2D TF diagrams generated using HT/WVD method

3.5. Experimental setup

An Intel Core i7 (2.80 GHz, 2808 MHz, 4 Cores, 8 Logical processors), RAM with 16 GB capacity, an NVIDIA GeForce GTX, and CUDA 9.0 is used together with 64-bit Windows 10. Using the computer language MATLAB (R2019a), the experiments were conducted. First the training data is considered, and the developed model is executed, later the test data is checked with the model and assessed the performance. The pre-trained ResNet50 is utilized, that forwards TF images to the fully connected layer which does the extaction of features, later passed to SVM. As part of classification, SVM Binary Classifier is used which successfully categorized the samples into Parkinson's affected and healthy controls. The computing power can be checked and enhanced depending on size of the dataset for future experiments.

4. RESULTS AND DISCUSSION

4.1. Evaluation metrics

As part of the result analysis, a confusion matrix [24] is generated that determines count of correctly classified instances and incorrectly classified instances. To measure the performance of the recommended approach, other metrics like F1 score as given in (5) is used, with the best score being 1, lowest being 0. Additionally, along with accuracy three other statistical indices like sensitivity, and specificity and precision are used for performance analysis [25].

$$F1Score = 2pr/\,(p + r) \quad (5)$$

where, 'p' is Precision and 'r'represents recall.

Whereas TP represents the count of PD signals categorized correctly with respect to the PD, FN represents the PD signals misclassified as belonging to the healthy control category. The TN is the quantity of healthy controls category signals not identified in the PD category. The number of signals that were wrongly assigned to the PD category in the healthy controls categories is known as the FP.

The system-generated confusion matrix is shown in Figure 9. Additionally, Figure 10 displays the system’s receiver operating curve. The TPR vs. FPR graph is called receiver operating characteristic (ROC) [26]. The PD and healthy controls categories’ area under the curve is 93.7%, which is a respectably low percentage.

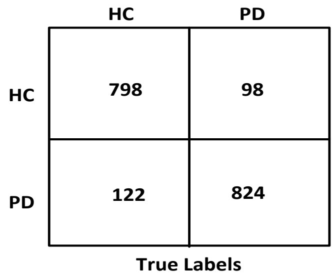

Figure 9. Confusion matrix

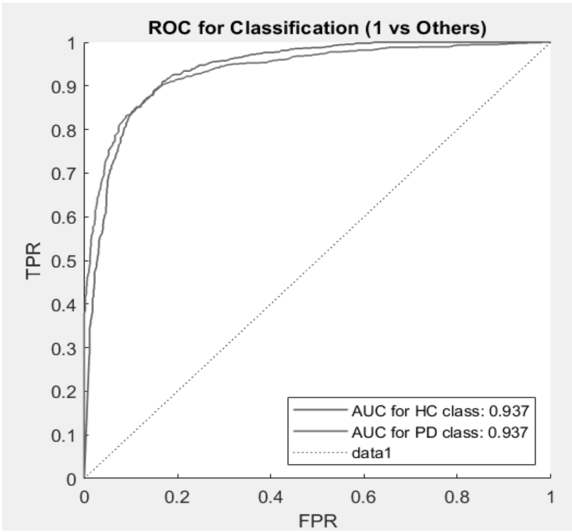

Figure 10. ROC generated for PD and HC classes

4.2. Classification results

The suggested method with the SVM classifier used a learning rate with value 0.001. Classification results for the test data achieved are as shown in Table 2. An accuracy of 92.13%, a precision of 93.76%, a sensitivity of 93.73%, and a specificity of 91.10%. The F1-Score achieved is 96.17% as well. Table 3 is comparison of accuracy with the other existing models. It is clear that the proposed model outperformed well and acheived better results.

Table 2. Classification results

Metric	Result achieved
Accuracy	92.13
Precision	93.76
Sensitivity	93.73
Specificity	91.10
F1-score	96.17

Table 3. Comparison of accuracies with other existing models

Methods	Accuracy
Existing approach [14]	86.86%
Existing approach [16]	81.24%
Proposed approach	92.13%

5. CONCLUSION

This proposed strategy consists of HT-WVD and transfers learning using SVM based on ResNet-50. The HT-WVD keeps time-domain characteristics. Additionally, transfer learning with ResNet-50 and SVM classifier is sufficient to use the capability of deep learning more fully than in previous research. It is observed that the 2D ResNet model is computationally costly compared to the suggested method, which is sophisticated than the current 1D CNN. This work offered new prospective methods for vocal feature analysis while demonstrating the viability of PD classification using speech-based data. Using 5-fold cross-validation (CV), the best accuracy of 92.13% was attained. Using the blind test interface, new PD patients in a clinic might be distinguished from healthy individuals. Comparing the recommended method to past studies, it does an excellent job classifying PD vocal signals.

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