# HYBRID MODEL FOR PREDICTING PARKINSON'S DISEASE FROM SPEECH AND HANDWRITING MODALITIES

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**KEYWORDS**

Root Fracture Detection, CBCT Imaging, Artificial Intelligence, Convolutional Neural Network (CNN), VGG19 Model, Automated Diagnosis, Dental Radiology, Diagnostic Accuracy, Sensitivity and Specificity, AI in Dentistry

**ABSTRACT**

Parkinson's disease is a central nervous system disorder that affects the movement of an individual. it has been observed that patients with parkinson's disease suffers from handwriting abnormalities, stooped posture, speech or voice disorders etc. The work was intended to implement a generalized machine learning model capable of predicting pd from the early stage symptoms. in this study, the speech datasets from uci machine learning repository and spiral and waves images from handwriting datasets were experimented to study the accuracy of the combination model. In order to improve the accuracy of prediction, the features extracted from the speech datasets were jitter,shimmer,nhr,dfa and ppe. also, the features extracted from handwriting datasets were pressure,grip angle,timestamp, radial velocity,speed etc. Different machine learning models like cnn, lstm,resnet etc were experimented on the above datasets. From the study, it was observed that a cnn/lstm model with proper hyper parameter tuning had worked well compared to other models being used in this work. the accuracy of cnn/lstm on the speech dataset was 88% and on the hand writing dataset was 92%..

# INTRODUCTION

Human brain (Prabal et al.,2023) is a highly complex system that controls motor skills, thoughts, emotions, anger etc. Neuroscience is an area which studies the functionalities of human brain. It deals with the study of functions and disorders of Nervous system. Some of the common neurological conditions associated with human brain are Parkinson's Disease (PD), Huntington's Disease (HD), Epilepsy etc. Among these, PD (Sasidharakurup et al.,2017) is a common disorder that affect the movement of an individual. It occurs due to the depletion of dopaminergic neurons in the Substantia Nigra, part of Basal Ganglia. There are various symptoms associated with early-stage diagnosis of the disease. Some of them are tremor in one hand, stooped posture, soft or slurred speech and micrographia.

Parkinson's diagnosis is still based on the clinical features like resting tremor, rigidity etc outlined by the Movement Disorder Society (Chandra et al.,2021). An automated diagnostic tool can help the neurologists in screening the condition easily. Moreover, an automation can even enhance the speed of disease detection. In the work(Dashtipour et al.,2018)(Thomas et al.,2017) two early-stage symptoms namely voice/speech signals and handwriting patterns were experimented with different machine learning models to predict PD.

Speech impairment in PD normally arise from motor and non-motor deficits. The current treatment options are limited despite the prevalence of motor speech disorders. Apart from the speech difficulty, language difficulty also prevails in PD patients. Speech therapy is the main treatment in such situations.

Similarly, another early-stage symptom of PD is micrographia. Since the deviations in the handwriting can be easily evaluated prior to other symptoms, the study on PD prediction from handwriting holds the potential to serve as an effective diagnostic tool for Parkinson's Disease. The tremors and rigidity of muscles makes the PD patient harder to draw smooth spirals and waves. So, these data can be examined for motor assessment(Ivey et al.,2012). Initially, gentle methods like spiral drawing pen paper and handwriting tests were adopted for PD assessment. PD patients can also improve the handwriting by the use of adaptive equipment, practicing certain exercises etc. The current study concentrates on utilizing the spiral and wave datasets for predicting neurological conditions.

Studies are underway to detect the early-stage prediction of PD from different modalities using traditional and deep models. Detecting handwriting biomarkers accurately may enhance the possibility of early stage diagnosis. Individuals with PD exhibits lower velocity and pressure on using a pen for sketching. In a related study (Drotár et al.,2014) the conventional model, SVM, achieved an accuracy of 85% with the assistance of feature extraction algorithms. Another work (Tallapureddy & Radha,2022) on the PaHaW datasets focused on learning the intensity of the disease. The previous work (Thakur et al.,2022) combines Dynamic and Static spiral test. Predictions with deep learning models are very popular nowadays (Alniemi et al.,2023). In the paper(Galli et al.,2014), the parameters were optimized with the Particle Swarm Optimization algorithm. The strength of Archimedean spiral tests for PD detection and prediction had been demonstrated by the researchers in(Lamba et al.,2021).

PD prediction from the speech signals has drawn attraction most recently. Voice recordings of early-stage PD patients in telemonitoring datasets were used for the previous study (Ranjan et al.,2023). The study revealed that the Least-squares support-vector machine exhibited superior performance in mapping the Unified Parkinson's Disease Rating Scale with vocal features. The draw backs of these works were high computation and overfitting of the model. In a similar work (Eskidere et al.,2012) features of speech signals were given to a multilayer NN to give a prediction accuracy of 91%(Liu et al.,2022). In the study(Renuka et al.,2022) an ensemble of CNNs was employed, contributing to the generation of promising results. In the work(Taleb et al.,2020), LSTM model was used for PD prediction from subject's voice samples. A combination model was experimented on the UCI Machine Learning repository datasets to get an accuracy of 85%(Rajeswari & Nair,2021).

Apart from the analysis of the previous studies on PD prediction from speech and handwriting modalities, the current work focused on elevating the accuracy of the Machine Learning model through feature extraction and integration of CNN/ LSTM architectures.

# METHODS

The initial procedure used in the ML training was the pre-processing of raw data (speech and hand writing). These data were normalised to a standard scale for an optimal learning. Later features were extracted from this data. The extracted features in the form of vectors were given to the models for classification. The model architecture was given in Fig.1.

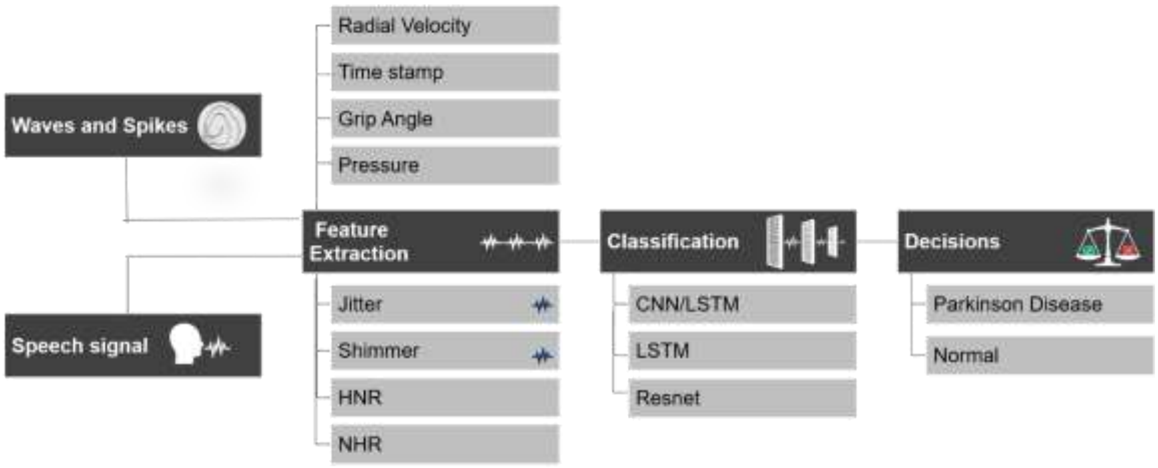


Fig 1. Model Architecture

## *FEATURE EXTRACTION*

### FEATURE EXTRACTION FROM SPEECH SIGNALS

Feature extraction is a vital step employed in machine learning to enhance recognition performance. Characteristics such as Shimmer, Jitter etc were extracted from speech signals through preprocessing methods like Vocal Fold Features and Mel Frequency Cepstral Coefficient (MFCC)(Rajeswari & Nair,2022). MFCC converts raw audio into a compact representation that captures important frequency and temporal information. In MFCC, the raw audio signal was converted into a digital signal with a sampling frequency of 16kHz. Pre-emphasis was done to increase the energy magnitude in the higher frequencies. Windowing helps to detect the phones in the speech. The time domain signals were converted into frequency domain signals by applying the Discrete Fourier Transform (DFT). Mel scale(Pedersen, 1965)was used to map actual frequency to the human perceive frequency. Eventually an inverse transform of the above signal was taken. MFCC model extract first 12 coefficients. The steps involved in feature extraction can be obtained from Fig.2.

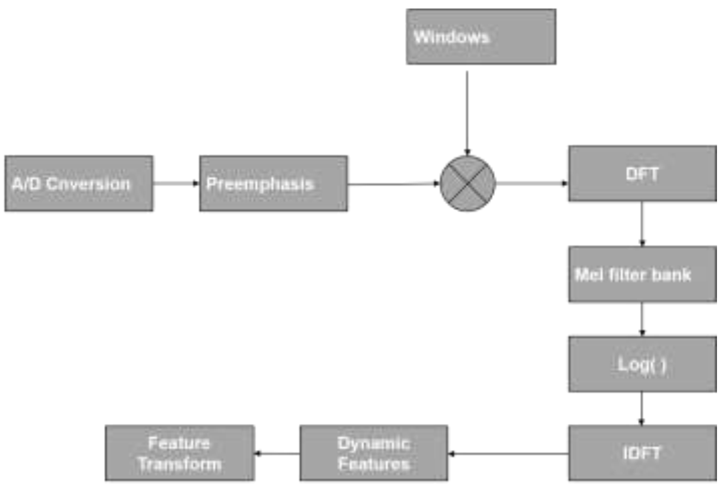


Fig 2. Feature Extraction using MFCC

## FEATURE EXTRACTION FROM HAND WRITINGS

In a related investigation (Kulkarineetham & Thananant,2023) the study analysed the writing patterns of individuals suffering from PD, focusing on jerk normalization concerning duration and size per stroke. The investigation revealed that the forward and backward strokes requiring the wrist and finger co-ordination exhibited huge jerks. This observation led to the conclusion that PD patients tend to exert more pressure and grip on the writing surface. In handwriting recognition, kinematic features encompass metrics such as the velocity, displacement, acceleration, number of strokes and jerks. Displacement provides an approximation of the pen trajectory. The velocity can be computed by taking the first derivative of displacement. The feature acceleration was extracted by taking the second derivative of displacement Similarly, feature jerk was extracted by taking the third derivative of displacement. Additionally, the feature Radial Velocity(Vessio,2019) was also extracted to improve the learning. It is defined as the rate of change of distance between the point and the object. It was obtained by dividing the displacement by the signed angle.

## *ALGORITHMS USED*

The current study focused on the analysis of different deep learning algorithms like CNN, LSTM and Transfer Learning model like Resnet.

Convolutional Neural Networks (CNNs) is good in image classification(Kamble et al.,2021), automatically detecting and identifying features without human intervention(Tiwari,2020). The CNN model comprises of three major layers. The convolution layer conducts a convolution operation between a restricted portion of the image and a learnable parameter known as the kernel. It facilitates parameter passing to higher layers and sparse interaction. The pooling layer aids in reducing the size of higher dimension data, thereby minimising the required weights and computation. The input to output layer mapping is done by the fully connected layer.

Long Short-Term Memory (LSTM) is a sequential model specifically designed for handling dynamic data. The different gates used in LSTM makes it superior to the basic Recurrent Neural Network (RNN)( Pereira,2018). Unlike RNN, LSTM is efficient to handle long term dependencies of data which makes them capable for speech recognition, language translation etc. It can hold information for an extended period in a memory cell. The memory cell in LSTM is governed by three gates. The input gate will decide on the information to be included in the memory. The forget gate deals with the data to be removed from the memory. Lastly, the output gate takes decision on the information to be expelled from the memory cell. LSTM is used in Time Series Forecasting, Speech Recognition etc. In the work(Sztahó et al.,2021), LSTM model was used for PD prediction from subject's voice samples.

Resnet-50(Men et al.,2021) is a deep pretrained model with 50 layers. In Neural Networks as the layers increases the training error decreases and over a period it starts increasing. Early stopping is introduced to avoid such situation. But in Resnet, the training error diminishes with the increase in layers. This pretrained model can classify images upto 1000 classes. The short cut connections in Resnet-50 provides identity mapping to make the network simpler. The high variability of handwriting in PD patients was studied in this work(Kamran et al.,2021)with the help of a Resnet-50 model.

In the present study, CNN/LTM was used to enhance the model's performance. Initially, features were extracted from the raw audio signals and handwriting images using the method outlined in the previous section. The distribution of data remained consistent between the train class and test class. The model was evaluated using Ten-fold cross-validation method, where 70% of the data was allocated for training and 30% for testing. All models were trained using the RMSprop optimizer, employing binary cross-entropy loss. The RMS prop optimizer converges to an optimal solution for less number of iterations. For both speech and handwriting data, batch size of 20 and number of epochs of 20 were chosen. A standard learning rate of 0.0001 was finalized after many trials. Pre-trained weights were used for the training of the Transfer Learning Model, Resnet. Here, the early layers were used in Transfer Learning and the latter layers in retraining. The evaluation of model's performance involved the use of Confusion Matrix. The Confusion Matrix visualizes the four major outcomes of classification. True Positive result occurs when a positive sample is correctly predicted by the model. False Negative result occurs when a positive sample is incorrectly predicted by the model. False Positive occurs when a negative sample is incorrectly identified, and True Negative is when negative samples are correctly identified by the classifier. The classification report serves as an additional performance metric, revealing crucial insights into Precision and Recall. Precision is a measure showing how many of the positive predictions are correct. Recall measures shows how good the model is at finding all the positives.

## *DATASETS*

The audio signals from Parkinson's Disease (PD) patients were sourced from the UCI Machine Learning Repository(Newman,1998). During the data collection process, microphones were set to a frequency of 44.1khz. About 188 patients suffering from PD and the age ranging from 33 to 87 contributed the data for this repository. All the clinically relevant features such as energy, shimmer, jitter etc were extracted for the study. The datasets used for hand writing recognition of PD patients were the spiral and wave drawing patterns using Digitized Graphics Tablet from the UCI Machine Learning Repository.

# RESULTS AND DISCUSSIONS

Most of the PD clinical diagnostic studies focused on single modality. In the current work, PD predictions were based on two modalities namely speech and handwriting. The objective of the work was to implement a model capable of producing better accuracy for different modalities of PD. The learning trends of the model, as illustrated in Fig.3, revealed that CNN/LSTM achieved an accuracy of 88%, while LSTM achieved an accuracy of 83% for speech signals. Considering the significance of other modalities in PD prediction, the study was extended to the static handwriting (HW) data. Initial experimentation focused on introducing the spiral/wave images directly to the Resnet model after preprocessing the images. But the model was able to produce an accuracy of only 66% with an increase in model loss. The feature extraction method facilitated the CNN/LSTM model in converging to an accuracy of 92%, as depicted in Fig.3,

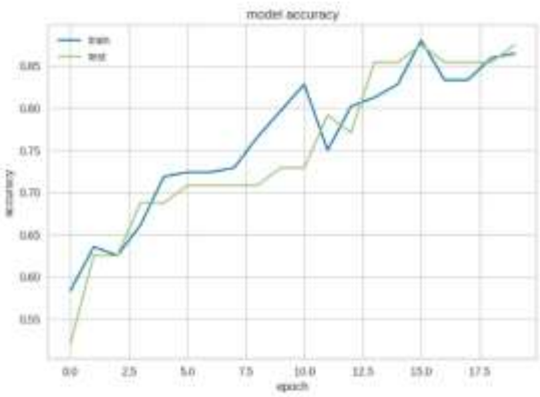


Fig.3.1. CNN/LSTM with an accuracy 88% (speech)

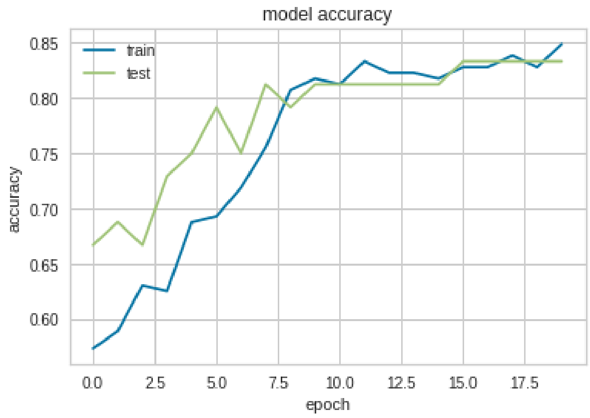


Fig.3.2. LSTM with an accuracy 83%(speech)

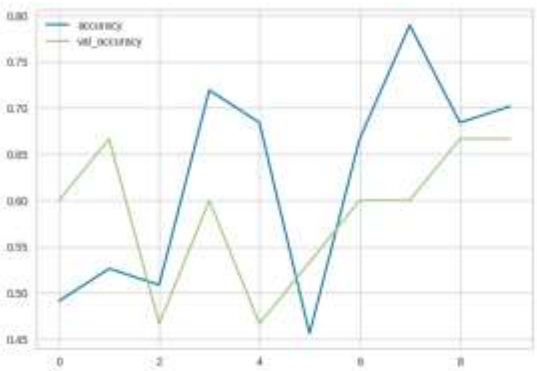


Fig. 3.3. Resnet-50 with an accuracy 66%(HW)

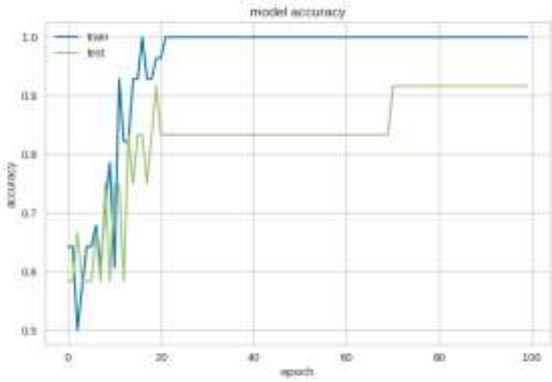


Fig.3.4. CNN/LSTM with an accuracy 92% (HW)

Fig 3. Learning Trends of the models

Various performance metrics such as the Confusion Matrix, Classification Report, and ROC Curves were employed in the study. The Confusion Matrix for the CNN/LSTM model (Table I) indicates that out of 48 test samples, 26 True Positive (TP) speech samples and 16 True Negative (TN) speech samples were correctly identified by the classifier. Similarly, for the LSTM model (Table II) with the same speech signals, TP and TN values were 25 and 15, respectively. The Confusion Matrix in Table III shows that 29 samples were correctly predicted. In contrast, Table IV reveals that only 19 samples were correctly predicted by the Resnet

Table I

CONFUSION MATRIX OF CNN/LSTM (speech)

| | ***Parkinson*** | ***Control*** | ***Rate(%)*** |
|---|---|---|---|
| Parkinson | 26 | 2 | 92 |
| Control | 4 | 16 | 88 |
| Precision (%) | 87 | 88 | |

Table II

CONFUSION MATRIX OF LSTM (speech)

| | ***Parkinson*** | ***Control*** | ***Rate(%)*** |
|---|---|---|---|
| Parkinson | 25 | 3 | 86 |
| Control | 5 | 15 | 70 |
| Precision (%) | 83 | 83 | |

Relying solely on accuracy graphs for model evaluation is inadequate. It is clearly evident in clinical data, where metrics such as Precision and Recall significantly contribute to gauging the model's accuracy. These measures of CNN/LSTM model were compared and studied in conjunction with other models. Precision is a measure showing how many of the positive predictions are correct. Recall measures shows how good the model is at finding all the positives. These details are shown in Table V and Table VI respectively.

Table III

CONFUSION MATRIX OF CNN/LSTM (HW)

| | ***Parkinson*** | ***Control*** | ***Rate(%)*** |
|---|---|---|---|
| Parkinson | ***15*** | ***1*** | ***92*** |
| Control | 0 | 14 | 100 |
| Precision (%) | 100 | 93 | |

Table IV

CONFUSION MATRIX OF Resnet (HW)

| | ***Parkinson*** | ***Control*** | ***Rate(%)*** |
|---|---|---|---|
| Parkinson | 6 | 9 | 66 |
| Control | 2 | 13 | 67 |
| Precision (%) | 75 | 59 | |

Table V

Comparison of Precision measures of the models

| ***Models*** | ***Parkinson*** | ***Control*** |
|---|---|---|
| ***CNN/LSTM(speech)*** | 87 | 89 |
| ***LSTM (speech)*** | 80 | 83 |
| ***CNN/LSTM(handwriting)*** | 100 | 93 |
| ***Resnet-50(handwriting)*** | 75 | 59 |

Table VI

Comparison of Recall measures of the models

| ***Models*** | ***Parkinson*** | ***Control*** |
|---|---|---|
| ***CNN/LSTM(speech)*** | 87 | 89 |
| ***LSTM (Speech)*** | 89 | 75 |
| ***CNN/LSTM(handwriting)*** | 100 | 83 |
| ***Resnet-50(handwriting)*** | 40 | 87 |

The ROC curve serves as a performance metric, evaluating the model's effectiveness based on the True Positive and False Positive Rate. The ROC comparison of CNN/LSTM with Resnet on handwriting datasets and ROC comparison of CNN/LSTM with LSTM on speech datasets were depicted in the Fig.4. From the graph, it was observed that the CNN/LSTM with high Area Under Curve (AUC) value of 0.92 (HW) and 0.88(speech) gives better prediction compared to other models.

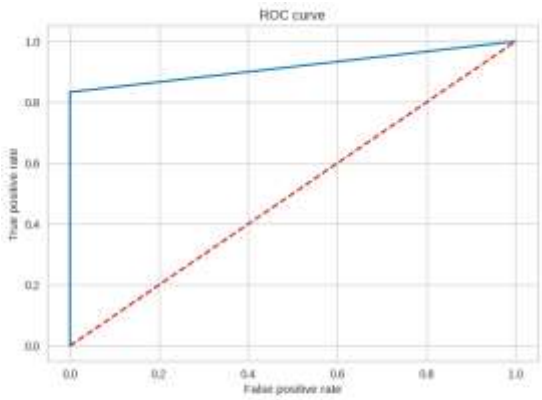


Fig 4.1 AUC=0.92 for HW (CNN/LSTM)

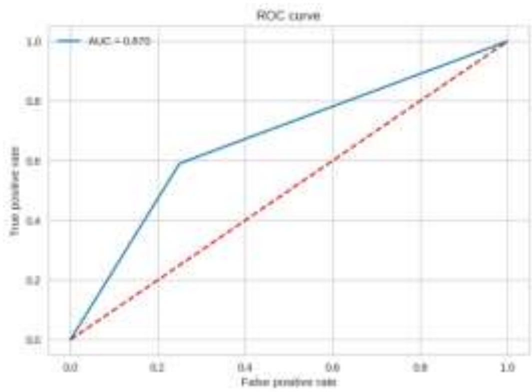


Fig 4.2 AUC=0.67 for HW (Resnet)

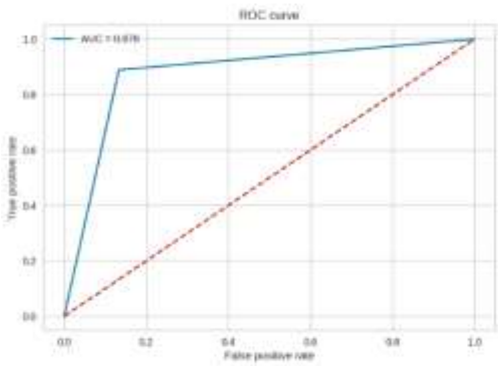


Fig.4.3 AUC =0.88 for Speech(CNN/LSTM)

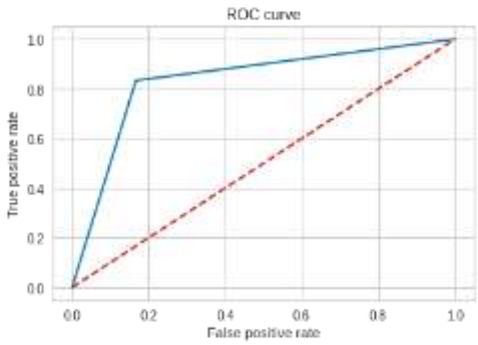


Fig.4.4 AUC =0.83 for Speech(CNN/LSTM)

Fig 4. ROC curve of CNN/LSTM model on speech and Handwriting datasets-The model with higher Area Under Curve value gives more accurate predictions.

From the graph plotted in Fig.5. it was observed that the model loss started increasing from the 10th epoch onwards leading to an accuracy of 92% for speech data and the model loss started increasing from 15th epoch onwards giving an accuracy of 88% for hand writing data. So, to mitigate the risk of model overfitting, an optimal value of 20 epochs was chosen.

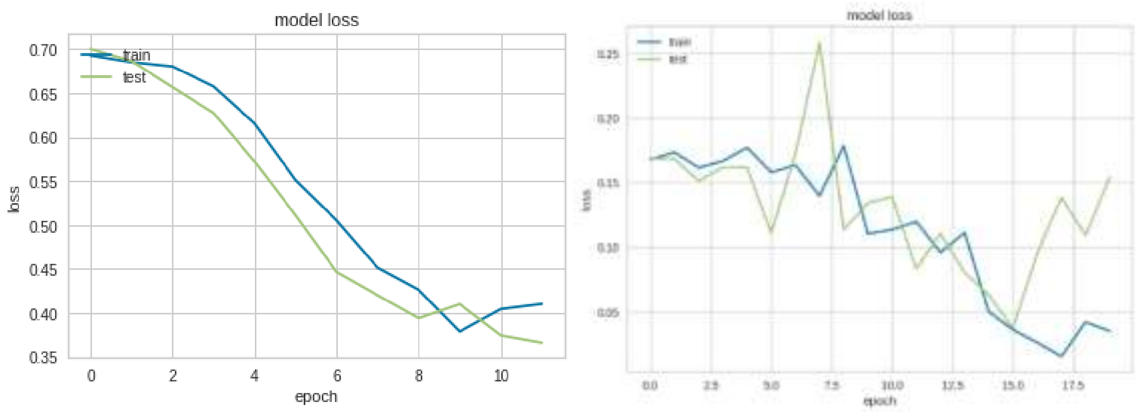


Fig.5. Model loss of CNN/LSTM model on speech and HW datasets

Based on the results, the conclusion was drawn that the CNN/LSTM achieved a commendable model accuracy of 92% for handwriting and 88% for speech signals. Thus, the CNN was successful in learning spatial features and the LSTM in learning the time dependent features.

# CONCLUSION

The current work focused on an optimised model capable of predicting Parkinson's Disease from two different modalities, Speech and Handwriting. Since these modalities are early-stage symptoms of the disease, detecting PD from these would help in the early-stage treatment. Experiments were conducted on different machine learning models like CNN, Resnet and LSTM. Hence, the study examined and identified the advantages of utilizing the benefits of CNN and LSTM. The CNN/LSTM model with hyperparameter tuning yielded improved accuracy for this type of data, achieving 88% for speech and 92% for handwriting. The study could be further extended to encompass other static and dynamic Parkinson's Disease (PD) modalities. Enhancing the model's robustness could be achieved by extracting more clinically relevant features and employing other ensemble methods.

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