PARKINSON'S DISEASE DETECTION USING CNN & MACHINE LEARNING TECHNIQUES

Submitted in partial fulfilment of the requirements for the award of the degree of

BACHELORS OF TECHNOLOGY

in

ELECTRONICS AND COMMUNICATION ENGINEERING

Submitted by

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(IEC2019004)

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CANDIDATE DECLARATION

I hereby declare that the work presented in this report entitled **"Parkinson's Disease Detection Using CNN & Machine Learning Techniques"**, submitted towards the fulfillment of BACHELOR'S THESIS report of **Electronics and Communication Engineering** at the Indian Institute of Information Technology Allahabad, is an authenticated record of our original work carried out under the guidance of **Dr Suneel Yadav.** Due acknowledgements have been made in the text for all other material used. The project was done in full compliance with the requirements and constraints of the prescribed curriculum.

Place: Prayagraj
Date:

(Animesh Roy)
IEC2019004

CERTIFICATE FROM SUPERVISOR

This is to certify that the statement made by the candidate is correct to the best of my knowledge and belief. The project titled **"Parkinson's Disease Detection Using CNN & Machine Learning Techniques"** is a record of candidates' work carried out by him under my guidance and supervision. I do hereby recommend that it should be accepted in the fulfillment of the requirements of the Bachelor's thesis at IIIT Allahabad.

Place: Prayagraj
Date:

Supervisor's Name & Signature

Dr Suneel Yadav
Assistant Professor

CERTIFICATE OF APPROVAL

The forgoing thesis is hereby approved as a creditable study carried out in the area of Electronics and presented in a manner satisfactory to warrant its acceptance as a pre-requisite to the degree for which it has been submitted. It is understood that by this approval the undersigned do not necessarily endorse or approve any statement made, opinion expressed or conclusion drawn therein, but approve the thesis only for the purpose for which it is submitted.

Committee on the final examination for the evaluation of the thesis:

1. Dr Suneel Yadav

Dean(A & R)

ACKNOWLEDGEMENT:

I am highly indebted to **Dr Suneel Yadav** and obliged for giving me the autonomy of functioning and experimenting with ideas. I would like to take this opportunity to express my profound gratitude to him not only for his academic guidance but also for his personal interest in my report and constant support coupled with confidence-boosting and motivating sessions which proved very fruitful and were instrumental in infusing self-assurance and trust within me. The nurturing and blossoming of the present work are mainly due to his valuable guidance, suggestions, astute judgement, constructive criticism and eye for perfection. My mentor always answered a myriad of my doubts with smiling graciousness and prodigious patience, never letting me feel that I am novices by always lending an ear to my views, appreciating and improving them and by giving me a free hand in my report. It's only because of his overwhelming interest and helpful attitude, the present work has attained the stage it has.

Finally, I am grateful to our Institution and colleagues whose constant encouragement served to renew my spirit, refocus my attention and energy and helped me in carrying out this work.

Date: Animesh Roy

ABSTRACT:

Parkinson's disease (PD) is a neurodegenerative disorder that affects millions of people worldwide. It mainly affects the motor system, the symptoms start to appear when the brain can't make enough dopamine to control movement properly. It develops when a particular part of the brain - called the substantia nigra - stops working properly and is lost over time. There are three main symptoms - tremors (shaking), slowness of movement and rigidity (muscle stiffness). This study presents two different approaches to detecting and classifying PD using two datasets. One is a Convolutional Neural Network (CNN) based model for analysing the drawing patterns of spiral sketches. Then the CNN model is compared with two other medical image datasets such as lung cancer and brain tumour. Another one is Machine Learning based models such as XGBoost, Logistic Regression, DecisionTree Classifer, and SVC for analysing the speech recordings of the patients. The overall classification accuracy resulting from the CNN model is 97.26% and the testing accuracy is 0.79, 0.82, 0.90 and 0.92 for XGBoost, Logistic Regression, DecisionTree Classifer, and SVC models respectively. Also, I have used KNN and RandomForest Classifier for the classification of the speech dataset.

CONTENTS:

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INTRODUCTION:

Parkinson's disease (PD) is a long-term degenerative disorder of the central nervous system mainly affecting the motor system. It develops when cells in a particular part of the brain - called the substantia nigra - stop working properly and are lost over time. Symptoms start to appear when the brain can't make enough dopamine to control movement properly. Typically, symptoms appear gradually, and as the condition progresses, non-motor symptoms increase in frequency. shaking rigidity, difficulty in motion, and trouble walking are the most noticeable early signs.

PD can lead to delayed motor activity, behavioural changes, sadness, anxiety, sleep difficulties, and sensory network impairments. Environment-related factors and genetic predisposition are two of the main causes of PD. According to WHO, in 2019, PD resulted in 5.8 million disability-adjusted life years, an increase of 81% since 2000, and caused 329,000 deaths, an increase of over 100% since 2000 [1].

One of the disorders for which there is currently no cure is PD. Therefore, the best course of action is to prevent the onset of this illness and determine through some experiments on this individual's audio if the individual is more vulnerable and if there is a potential for infection.

A complicated and skilful coordinated motor action is spiral sketching. As a result, it is used as a sensitive motor evaluation and a screening tool for early PD symptoms. Also, the deflections in the voice, reduced voice and generally a low-volume noise with a monotone quality can be used for detecting PD. In this project, Convolutional Neural Network (CNN) based model can be used for analysing the drawing patterns of spiral sketches and Machine Learning models such as Logistic Regression, DecisionTree Classifier, SVC, KNN and XGBoost for audio signals feature to predict whether the person is healthy or not.

The following is a description of the inspiration for this work:

For the condition to be effectively treated and managed, early identification of PD is essential. In a real-world setting, PD is detected through a variety of medical tests, including spiral drawing and speech characteristics. Due to repeated examinations, it can frequently take an enormous amount of time and resources to diagnose a person with PD. In the medical industry, this project acts as the neural network-based model for PD detection methods that could result in an early diagnosis of PD. Additionally, DL-based models can offer medical aid and direct physicians in the early identification of PD, which will extend the patient's life using cutting-edge drugs.

LITERATURE SURVEY:

In This literature survey, we focus on the use of Convolutional Neural Networks (CNN) and Machine Learning for Parkinson's Disease Detection. We review recent research studies that employ these techniques for the diagnosis, classification, and prediction of PD.

a. Hand Sketch Data for PD Detection and Classification:

For the purpose of gathering information on mobility disorders like PD, wearable sensors have gained popularity. The following scientists have assessed or identified PD using this technique. For the diagnosis and staging of PD, handwriting and sensory datasets were subjected to cutting-edge machine learning and deep learning techniques. While essential tremor (ET) and Parkinson's disease (PD) share several clinical characteristics, such as movement and gait, Moon and their fellow researchers used in their study a variety of machine-learning techniques to distinguish between the two diseases [3]. These techniques included ANNs, SVM, KNN, decision trees, random forests, and gradient boosting.

El Maachi and fellow researchers used a deep learning architecture approach in [4] to extract pertinent data for the diagnosis of Parkinson's disease (PD) using gait classification. 18 parallel 1D-CNNs with a total of 4 layers of convolution, two pooling (max-pool) layers, and one ANN layer make up the first section of the network. The combined outputs of the one-dimensional CNNs are coupled by a fully connected network in the proposed framework's second component to produce a final classification. For categorising the PD data into five phases or controls, the ANN layer consists of two completely linked layers, a result layer, and either five neurons or one neuron. The proposed framework has an accuracy of 98.7% in differentiating PD from controls and an accuracy of 85.3% in predicting the level of severity of the UPDRS for people.

Shaban investigated combining wave and spiral writing samples to train an adjusted pre-trained VGG-19 to distinguish between controls and PD [5]. The proposed model achieved an accuracy and sensitivity of about 88% and 86%, respectively. Naseer and fellow researchers presented a deep learning strategy based on AlexNet to recognise PD subjects using handwriting data via transfer learning, augmenting data, freezing, and tweaking [6]. The accuracy obtained using this method with the PaHaW data, which included 36 PD patients and 36 controls, was 98.28%.

A deep learning framework based on configurable networks that have been trained including AlexNet, GoogleNet, VGG-16, VGG-19, ResNet-50, and ResNet-101 in addition to the same models created from scratch was offered by Kamran and colleagues [7] to divide participants into normal and patients with PD. This study included a number of datasets, notably PaHaW, HandPD, NewHandPD, and Parkinson's drawings. Additional data augmentation techniques included flipping, rotating, lighting, contrast, and thresholding. On three separate handwritten

datasets, the refined AlexNet algorithm produced the best accuracy of 99.2%. This is an improvement over the most recent techniques.

b. Speech Samples for PD Detection and Classification:

A description of the cutting-edge machine learning and deep learning techniques used on the speech dataset modality for the diagnosis and staging of PD. For the purpose of classifying the raw speech of 43 PD sufferers and 9 controls, Frid et al. created a 4-layer CNN [8]. The suggested model demonstrated a high level of accuracy of up to 85% in differentiating between different phases of PD. In [9], Tsanas et al. used 132 dysphonia measurements to categorise the speech waveforms of 33 Parkinson's disease (PD) patients and 10 controls using SVM and random forest models. It was possible to identify PD with 99% classification accuracy using just 10 dysphonia features.

Two deep learning architectures were proposed by Gunduz et al. in [10] to categorise speech samples from 188 Parkinson's Disease patients and 64 healthy patients. The initial framework combined various elements that were retrieved from voice data before feeding them to a 9-layer CNN. Zhang and fellow researchers proposed an ML-based method in [11] that applies the time and frequency properties of speech data to a stacked autoencoder and the k-nearest neighbours (KNN) algorithm. Based on the Oxford and Istanbul datasets, the model detected PD with an accuracy of 94% to 98%.

METHODOLOGY:

The goal of this study is to propose a two-pronged strategy for the identification and classification of Parkinson's disease. These two approaches are as follows:

a. Using Spiral Drawing:

A complicated and skilful coordinated motor action is spiral sketching. As a result, it is used as an accurate motor analysis and a screening tool for early PD symptoms. Due to sluggish motor movements and reduced hand-brain coordination, the spiral sketched by someone with PD will significantly vary from an ideal spiral form and seem distorted. The whole process can be described as follows:

1. Data Preprocessing:

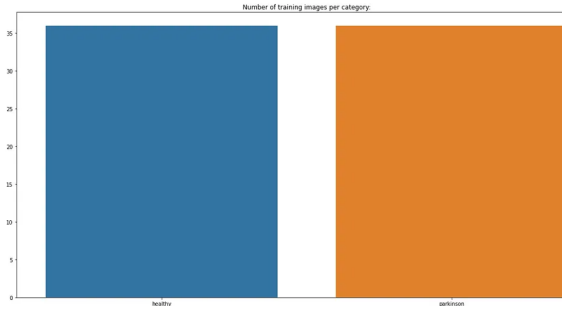

Fig. 1.1 Number of training images per category

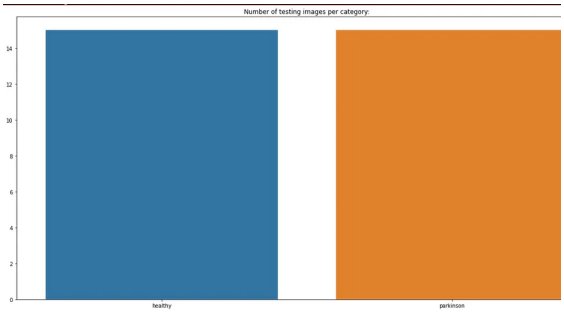

Fig. 1.2 Number of testing images per category

Images in the dataset are resized to a standard size (128, 128, 3). The dataset has been balanced, as can be observed. In both the train and test sets, the dataset has fewer images per category. So, the data augmentation of the dataset has been done to artificially create images for training and testing.

2. Data Augmentation:

Here, fresh images are generated using ImageDataGenerator. Since the images are spirals, they may be rotated in any direction without altering their meaning, hence the revolving limit is set at 360 degrees. Before the dataset is fitted to a model, the images are further standardised. The data distribution after the augmentation is -

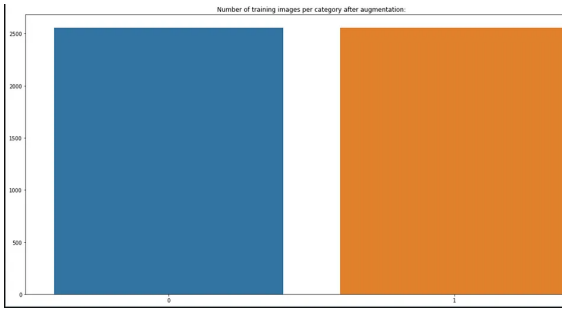

Fig. 2.1 Number of training images per category afte data augmentation

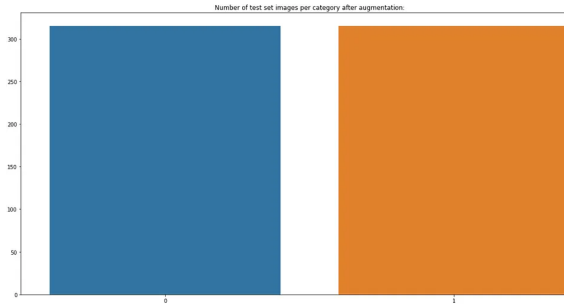

Fig. 2.2 Number of test images per category after dat augmentation

3. Training the CNN model:

The model architecture used in the implementation is a CNN model with the following features:

1. Four convolutional layers with 128, 64, 32, and 32 filters each are present in the model.
2. There are filters with different filter sizes in the convolutional layers.
3. Each convolutional layer is followed by a MaxPool2D layer.
4. The convolutional block is followed by one fully linked layer.
5. The last layer includes 2 channels for 2 classifications with softmax function.

Using Adam optimiser, the model is trained at a learning rate of 3.15e-5. Epochs have been set to 50.

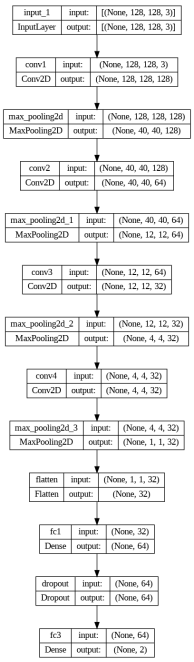

Fig. 3 Summary of CNN Mode

b. Using Speech Samples:

As most ML models converge significantly faster if the proportions of the parts are the same, it is crucial to standardise the training data and test data. The feature's mean will be balanced between 0 and 1 after standardising is completed. The distribution of the data will follow the normal pattern. We will use sklearn's StandardScaler to determine the mean and standard deviation of the property and then apply the following algorithm to each observation/value.

Splitting the dataset is the last step before we train our models. To randomly divide this data into a training set and a testing set, I used an 80/20 split to train vs test cases. This is necessary so that we can forecast the set of test data (unseen data) and estimate the predicted result of our model.

RESULTS:

a. Using Spiral Drawing:

The model's performance measurements are the Loss and Accuracy Plots.

The Accuracy and Loss Plots are given below:

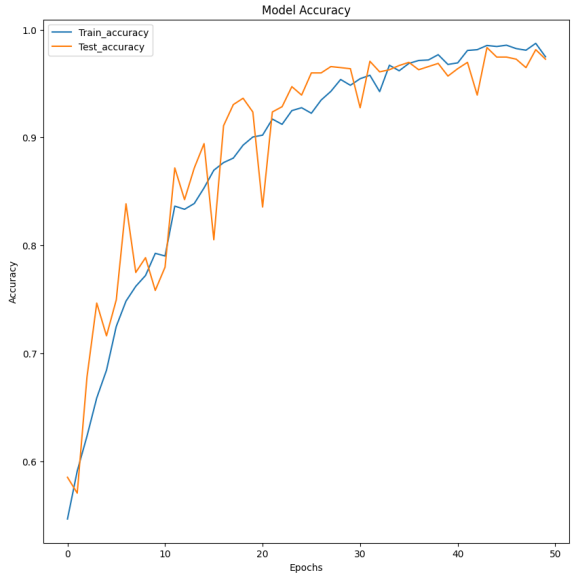

Fig. 4.1 Plot of Train and Test Accuracy of CNN

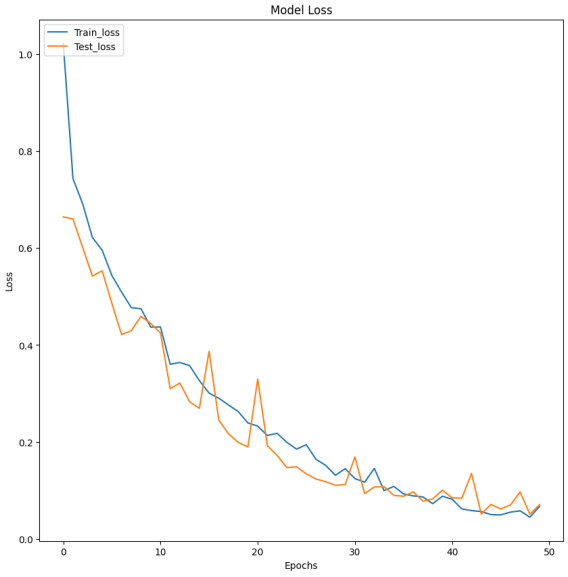

Fig. 4.2 Plot of Train and Test Loss of CNN Model

After evaluating of validation dataset got a Loss of 0.07 and an Accuracy of 0.97.

```
model.evaluate(val_data)
```

```
32/32 [==============================] - 1s 23ms/step - loss: 0.0708 - accuracy: 0.9726
[0.07083631306886673, 0.9726027250289917]
```

Fig. 5 Evaluation of Validation Data

b. Comparing the CNN model with other Medical datasets:

1. Brain Tumor Dataset:

Fig. 6.1 Plot of Train and Test Accuracy of Brain Tumor Dataset

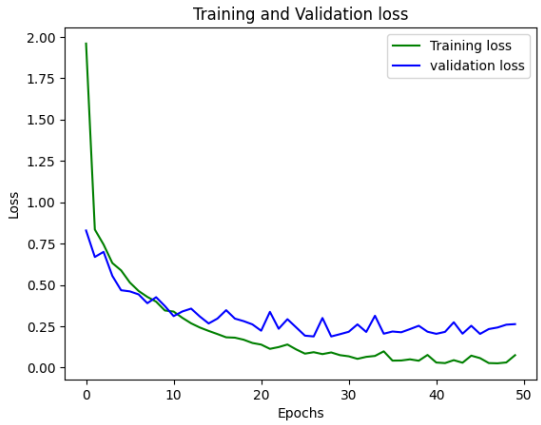

Fig. 6.2 Plot of Train and Test Loss of Brain Tumor Dataset

Validation Loss: 0.27

Validation Accuracy: 0.93

2. Lung Cancer Dataset:

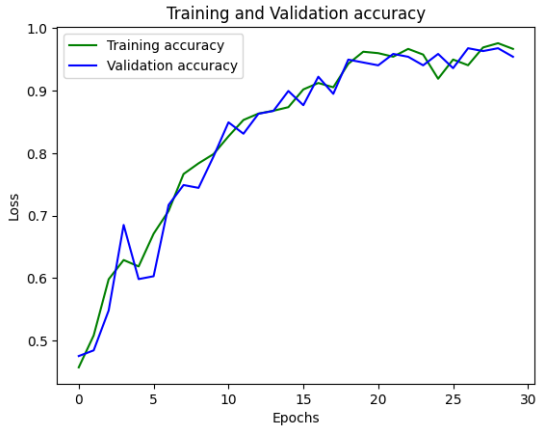

Fig. 7.1 Plot of Train and Test Accuracy of Lung Cancer Dataset

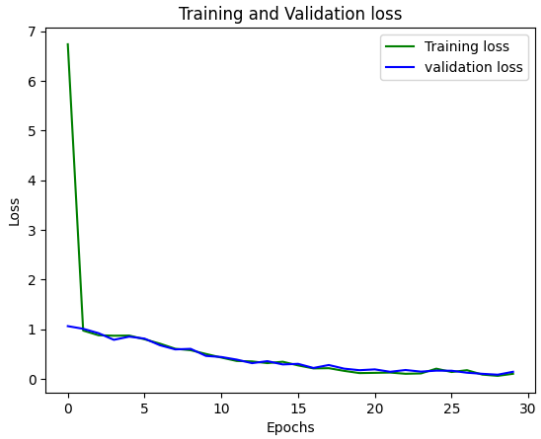

Fig. 7.2 Plot of Train and Test Loss of Lung Cancer Dataset

Validation Loss: 0.14

Validation Accuracy: 0.95

c. Using Speech Samples:

After analysing the performance and precision of the ML model, based on the estimation, we can observe that the model can predict from Logistic Regression is 0.79, XGBoost is 0.82, Decision Tree is 0.87 and SVC is 0.92.

Machine Learning Models	Accuracy of Training Set	Accuracy of Test set
Logistic Regression	0.88	0.79
XGBoost	1.00	0.82
DecisionTree Classifier	1.00	0.90
SVC	0.89	0.92

Fig. 8 Table of Accuracy of Training and Test Set using Various Machine Learning Models

Classification Report:

SVC:

	precision	recall	f1-score	support
0	0.69	0.75	0.72	12
1	0.88	0.85	0.87	27
accuracy			0.82	39
macro avg	0.79	0.80	0.79	39
weighted avg	0.83	0.82	0.82	39

RandomForest Classifier:

	precision	recall	f1-score	support
0	0.91	0.83	0.87	12
1	0.93	0.96	0.95	27
accuracy			0.92	39
macro avg	0.92	0.90	0.91	39
weighted avg	0.92	0.92	0.92	39

DecisionTree Classifier:

	precision	recall	f1-score	support
0	0.67	0.83	0.74	12
1	0.92	0.81	0.86	27
accuracy			0.82	39
macro avg	0.79	0.82	0.80	39
weighted avg	0.84	0.82	0.83	39

KNN:

	precision	recall	f1-score	support
0	0.88	0.58	0.70	12
1	0.84	0.96	0.90	27
accuracy			0.85	39
macro avg	0.86	0.77	0.80	39
weighted avg	0.85	0.85	0.84	39

Fig. 9 Table of Classification Report of Various Machine Learning Models

Correlation Matrix of the speech dataset:

Strong clusters of correlation between the variables are visible. For instance, there is a good correlation between Shimmer and Jitter variables and a substantial correlation between measures of Jitter. Additionally, there is a significant inverse relationship between HNR and the other

factors. Due to the non-linear nature of the novel measurements, such as RPDE, DFA, PPE, etc., there is little correlation between them.

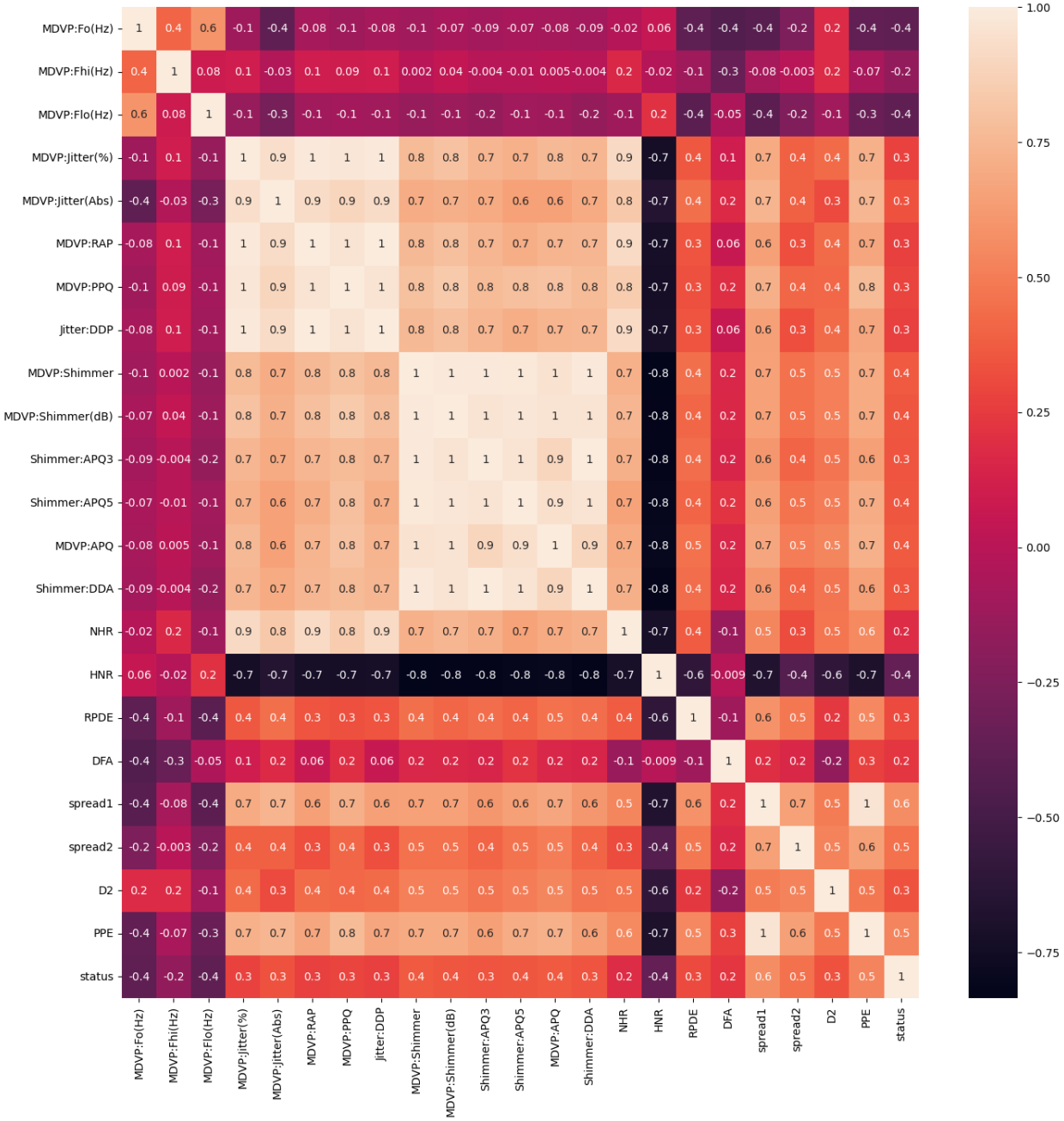

Fig. 10 Correlation Matrix of Speech Dataset

CONCLUSION:

In addition to using Spiral Drawing and Speech characteristics as an initial test for Parkinson's disease identification, this project gives a brief explanation of PD and its causes. In order to facilitate deployment on edge devices, the project attempts to optimise the model by keeping the total number of variables under 250k. The deployment to edge devices or less computationally efficient devices offers a solution for PD detection using CNN. It is crucial to remember that additional study is required to confirm this strategy's efficacy in bigger, more diverse groups. Additionally, CNNs should be used in conjunction with other diagnostic techniques rather than as the only tool for the diagnosis of Parkinson's disease.

FUTURE WORK:

This paperwork can be further extended for the following scenarios,

1. Large dataset: It is crucial to evaluate CNNs and machine learning methods on larger and more varied datasets in order to confirm their efficacy for detecting Parkinson's disease. This will guarantee that the models are reliable and precise for a variety of patients.
2. Multi-modal analysis: Spiral drawings are a potential method for Parkinson's disease identification, however, there may be other modalities that may be employed in addition to CNNs and machine learning strategies to increase accuracy. Gait analysis and speech analysis, for instance, could offer further details that could be utilised to increase the accuracy of a diagnosis.
3. Clinical translation: Although the application of CNNs and machine learning methods for Parkinson's disease identification is promising, it is crucial to make sure that these methods can be applied in clinical settings. To create tools and techniques that are accessible in clinical settings and user-friendly, researchers and clinicians will need to work together.

DATASET:

a. Spiral Drawing:

The original paper's image dataset was employed in the study [2]. The collection includes spiral wave wings made by Parkinson's disease patients and healthy individuals. Only spiral sketches are used in this study for classification. We must manually divide the dataset because it consists of both the Train Set and the Test Set.

Fig. 11.1 Spiral Drawing by a Healthy Person

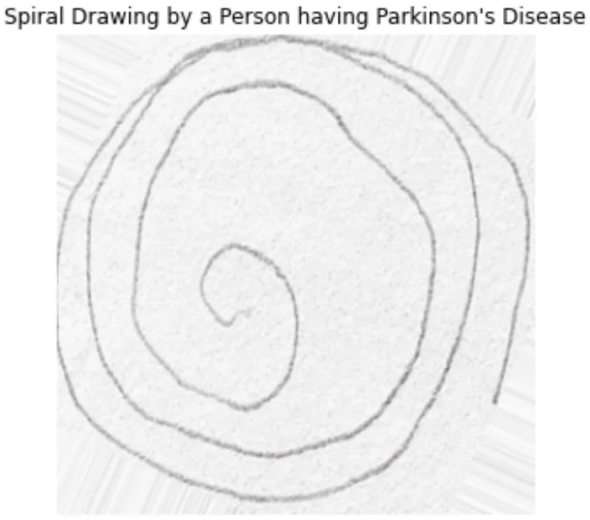

Fig. 11.2 Spiral Drawing by a Person having PD

b. Speech Samples:

The dataset of speech samples includes 31 patients. 23 patients have PD, and the rest are healthy people. Column (the "name" column) of the dataset indicates a particular voice measure and rows in the dataset suggest one of the 195 speech records from the individuals. The main focus of the dataset is to identify or differentiate healthy people and people with PD, as indicated by the "status" column, which has an integer value of 0 for healthy and 1 for PD.

Matrix column entries (attributes):

Attributes	Functionality
Name	Participant name and record number in ASCII
MDVP: Fo(Hz)	Average vocal fundamental frequency
MDVP: Fhi(Hz)	Maximum vocal fundamental frequency
MDVP: Flo(Hz)	Minimum vocal fundamental frequency
MDVP: Jitter(%), MDVP: Jitter(Abs), MDVP: RAP, MDVP: PPQ, Jitter: DDP	multiple ways to measure fundamental frequency fluctuation
MDVP: Shimmer, MDVP: Shimmer(dB), Shimmer: APQ3, Shimmer: APQ5, MDVP: APQ, Shimmer: DDA	Multiple ways to measures of amplitude fluctuation
NHR, HNR	Two measurements of the voice's noise tonal component ratio
Status	1 (one) means the person with PD, 0 (zero) mean healthy person
RPDE, D2	Two indices of the complexity of nonlinear dynamics
DFA	Exponent of signal fractal scaling
Spread1, spread2, PPE	Three nonlinear ways to monitor variations in fundamental frequency.

Fig. 12 Matrix Column Entries of Speech Dataset

The UCI Donald Bren School of Information & Computer Sciences provided the speech samples. The dataset comprises 195 items and 24 columns. Status is the dependent variable, whereas the variables MDVP: Fo(Hz) to PPE are independent. Note that voice files of the individuals have been analyzed and voice-related characteristics derived from voice recordings have been provided. The information is in CSV ASCII format. One instance per voice recording is present in each row of the CSV file. Each patient has six recordings, and the first column lists the patient's name.

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 195 entries, 0 to 194
Data columns (total 23 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   MDVP:Fo(Hz)       195 non-null    float64
 1   MDVP:Fhi(Hz)      195 non-null    float64
 2   MDVP:Flo(Hz)      195 non-null    float64
 3   MDVP:Jitter(%)    195 non-null    float64
 4   MDVP:Jitter(Abs)  195 non-null    float64
 5   MDVP:RAP          195 non-null    float64
 6   MDVP:PPQ          195 non-null    float64
 7   Jitter:DDP        195 non-null    float64
 8   MDVP:Shimmer      195 non-null    float64
 9   MDVP:Shimmer(dB)  195 non-null    float64
 10  Shimmer:APQ3      195 non-null    float64
 11  Shimmer:APQ5      195 non-null    float64
 12  MDVP:APQ          195 non-null    float64
 13  Shimmer:DDA       195 non-null    float64
 14  NHR               195 non-null    float64
 15  HNR               195 non-null    float64
 16  status            195 non-null    int64  
 17  RPDE              195 non-null    float64
 18  DFA               195 non-null    float64
 19  spread1           195 non-null    float64
 20  spread2           195 non-null    float64
 21  D2                195 non-null    float64
 22  PPE               195 non-null    float64
dtypes: float64(22), int64(1)
memory usage: 35.2 KB
```

Fig. 13 Summary of Speech Dataset

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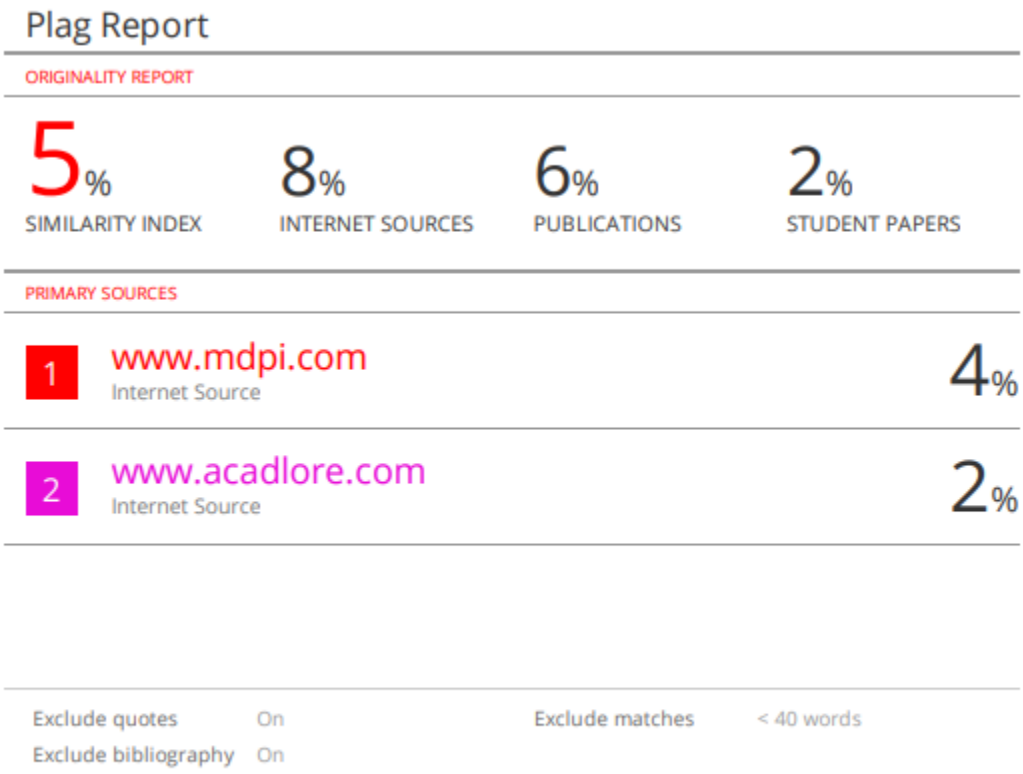
PLAGIARISM REPORT:



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