Bachelor of Technology

Project Presentation

Department of Computer Engineering
Sardar Patel Institute of Technology
(Autonomous Institute Affiliated to University of Mumbai)
Munshi Nagar, Andheri(W), Mumbai-400058
2020-21

A PRESENTATION ON

"NON INVASIVE PREDICTION OF PARKINSON'S DISEASE"

By

JINANG GANDHI (2017130019)
AUMKAR GADEKAR (2017130023)
TANIA RAJABALLY (2017130047)

Under the guidance of

DR. PREETI JANI

Introduction

- Parkinson’s disease is a neurodegenerative disorder.
- Early symptoms gradually develop into movement disorders.
- No proper laboratory test
- Recognising the symptoms at an early stage is of prime importance.

Motivation

- Parkinson’s is a disease affecting 700000 plus people in India
- Many people lack access to doctors
- Suffering can be reduced if diagnosed early
- The early diagnosis can help in the treatment of the patient
- A solution which allows people to test themselves for symptoms of Parkinson’s anywhere, anytime is required
- Since the disease has numerous symptoms, various combinations of tests can be tried

Objectives

- We aim to develop a non invasive system that would detect Parkinson's disease
- To research extensively on previous work and ascertain which features are best discriminators of healthy people and subjects with Parkinson's
- To employ a multi-modal approach to pick on various biomarkers, covering more symptoms
- To provide a convenient, user friendly and portable system mechanism
- To deploy the application on Appstore and Playstore

Literature Survey

Title	Details
Tracing and Handwriting: Refining parkinsons neurological disorder identification through deep transfer learning,"Neural Computing and Applications" [1] (2020)	• Implements Transfer Learning on Handwriting images • Accuracy: 98.28% • Fine tuned AlexNet model and AlexNet Freeze model on ImageNet and MINST datasets • Concludes that best accuracy is observed for Spiral trace images • We infer that customization with transfer learning can yield more accurate results
Tracing: Improved Spiral Test Using Digitized Graphics Tablet for Monitoring Parkinson's Disease [2] (2014)	• Uses a special graphics tablet, requires stylus pen • Speed and acceleration are recorded • Introduces a new test: Dynamic Spiral Test ○ Tests memory and tremors • Shows that correlation of acceleration between SST and DST is an important metric for classification
Speech: Prediction of Parkinson's Disease using Data Mining [3] (2017)	• Uses Praat script to convert the voice recording into voice report consisting of jitter, shimmer, frequency and other features • These parameters measure the deviation from standard voice sample • Decision tree for feature selection, K means for PD severity label • Accuracy between 88% to 94% • High accuracy is achieved even after considering less features indicating robustness of the approach

Literature Survey

Title	Details
Speech: Testing the assumptions of linear prediction analysis in normal words [4] (2006)	• Uses vowels to generate time series by Markov process • Voice sample classification for any disorder • Shows that non linear models work better on time series and speech as compared to linear models • A complex but highly accurate novel approach for voice sample analysis is explored here
Survey: mHealth Technologies towards Parkinson's Disease Detection and Monitoring in Daily Life: A Comprehensive Review [5] (2020)	• Impaired gait and balance - gyroscope and accelerometer • Vocal impairment - pitch, jitter, shimmer, repetitions • Tremors + Speed - Handwriting, tracing, finger tapping • Sleep disorder - gyroscope, accelerometer, gyrometer • Mood disorder - gyroscope, emotion detection from speech • Inferred that tests for multiple symptoms aids in effective classification
Mobile Application: Detecting and monitoring the symptoms of parkinson's disease using smartphones: A pilot study [6] (2015)	• A multitest (handwriting, speech, gait, reaction) smartphone application is developed in this system • Pilot study on limited data; Sensitivity 96.2%, Specificity 96.9% • Random Forest classifier to output UPDRS score (11-34) • Shows the effectiveness of mData for PD classification Emphasises on larger scale assessments; passive monitoring for future scope

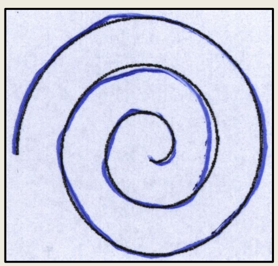
Gaps/Issues Identified

- Current implementations → Single test / special hardware [2]
- Common symptoms can lead to misdiagnosis
- Computer based systems are inconvenient for the elderly
- Voice based systems → Language specific data [3][4][9][11]
- High computing → Not suitable for mobile applications [12][13][15]
- Pilot studies were trained on very limited data

Problem Statement

- A non invasive, multi modal system for prediction of Parkinson's disease in the form of a portable, user friendly mobile application.

Mobile Application

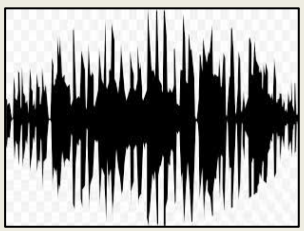


Tracing Test

Check for deviation and speed, etc.

Speech Test

Use phonetics for frequency, jitter



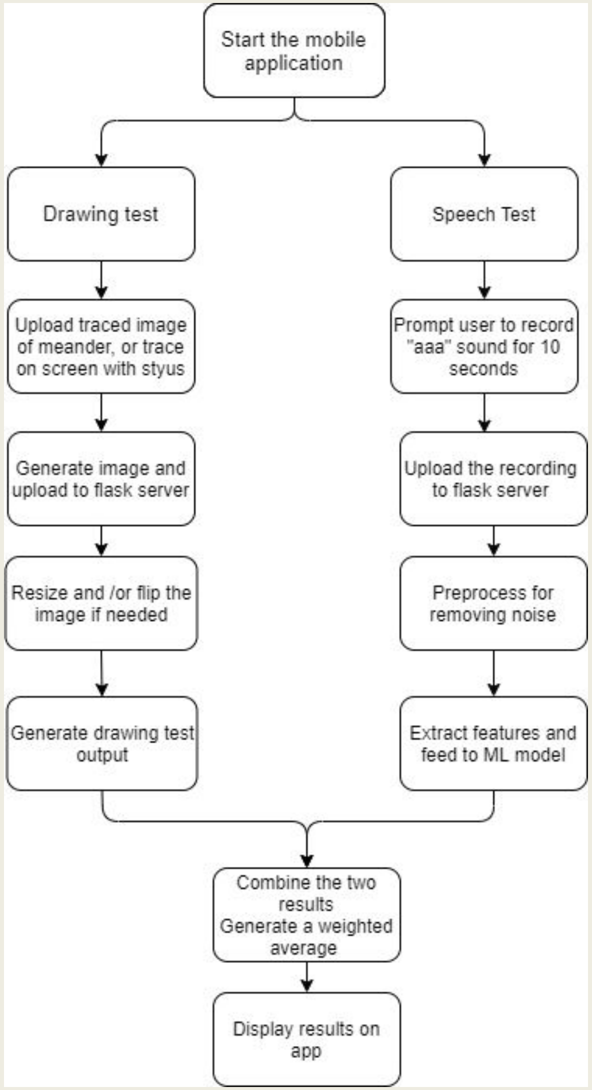
Weighted Average of both the predictions

Final prediction displayed to user

Contributions

- Most of the existing mobile applications focus on the therapy of Parkinson's Disease rather than its detection. Our system will provide with early detection of the disease.
- Robust, user-friendly and one of a kind application which will be affordable to the masses.
- Will consider various symptoms to provide accurate analysis.

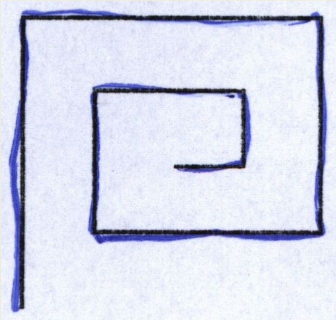
Proposed Design/ Method/ Mathematical Model



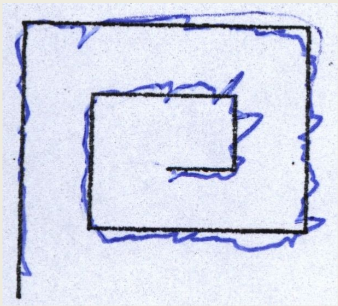
Implementation (Trace Test)

DATASET

- NewHandPD Dataset consists of spiral and meander images.
- It consist of images for different trace shapes of the PD and Control group participants.
- Meander images were used for model training.
- 264 images with even distribution between gender.



Tracing of Healthy Control



Tracing of PD Patient

Implementation (Trace Test)

MODEL FOR TRAINING

- A Convolutional Neural Network Model was used.
- Different models such as Inceptionv3, Xception, ResNet, VGG16, VGG19 and MobileNet were used to fit the data using transfer learning.
- The models were pre-trained on the ImageNet dataset.
- Augmentation (horizontal and vertical flip) was done.
- Images were resized to 224x224 pixels or 299x299 pixels depending on the model.
- Custom layers were added on the top of the layers of the pretrained model.

Implementation (Trace Test)

EXPERIMENTAL RESULTS

Accuracy obtained on Spiral Images

Model	Epochs	Augmentation	Training Accuracy	Testing Accuracy
MobileNet	15	Yes	85.88	81.08
Inception	15	Yes	84.73	79.73
Inception	15	No	94	83.23
Xception	15	Yes	92.75	81.08
VGG19	15	Yes	89.93	74.32
VGG19	15	No	98.21	83.01
VGG16	15	Yes	92.75	83.78

Implementation (Trace Test)

EXPERIMENTAL RESULTS

Accuracy obtained on Meander Images

Model	Epochs	Augmenta tion	Training Accuracy	Testing Accuracy
Inception	15	No	78.67	81.13
VGG19	15	Yes	99.18	97.39
VGG16	15	No	98	94.34
ResNet	15	No	98.58	90.57

Implementation (Trace Test)

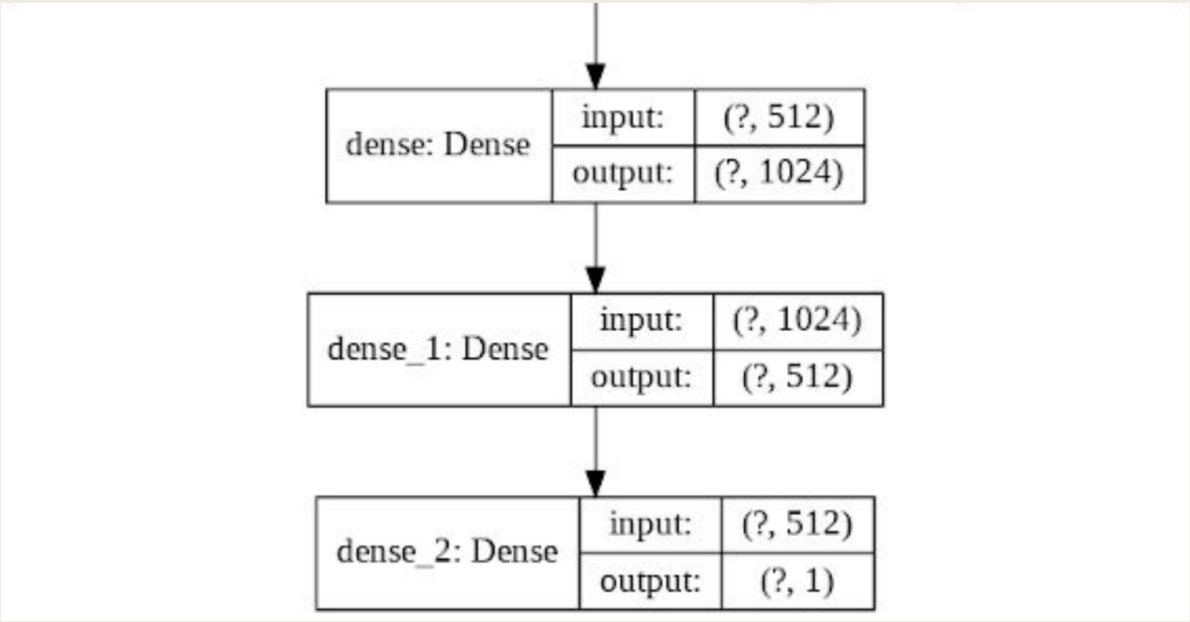
EXPERIMENTAL RESULTS

- VGG19 model with 15 epochs and augmented data on meander images showed the highest accuracy and low false negatives.
- VGG19 model consists of a set of 26 layers.
- We added 3 custom layers :
    - Dense Layer (1024 nodes) - ReLu activation
    - Dense Layer (512 nodes) - ReLu activation
    - Dense Layer (1 node) - Sigmoid activation
- For compiling, Adam optimizer was used.
- Loss was calculated using Binary Cross-Entropy Loss function.
- The score output indicates the likeliness of PD.

Implementation (Trace Test)

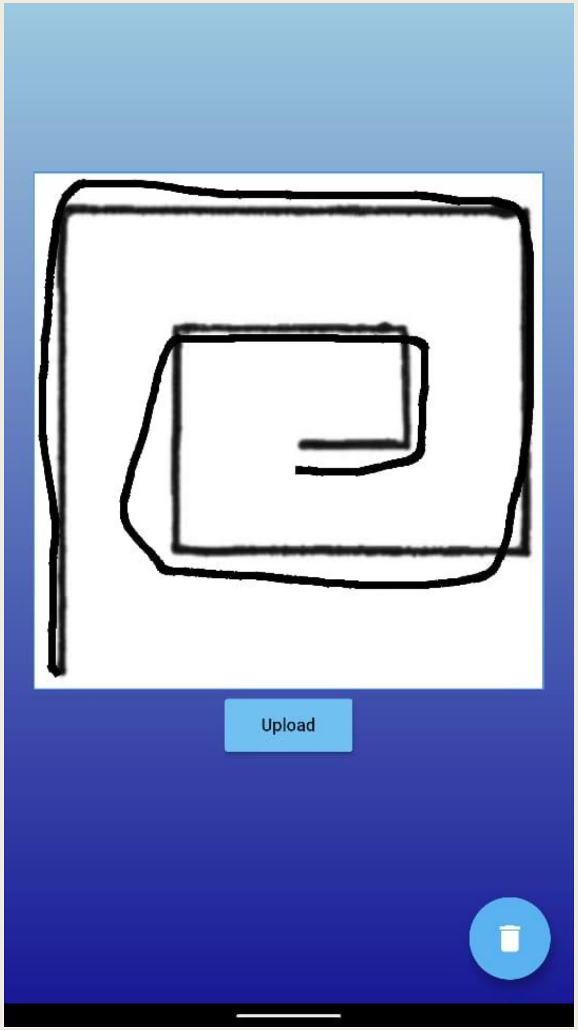
EXPERIMENTAL RESULTS

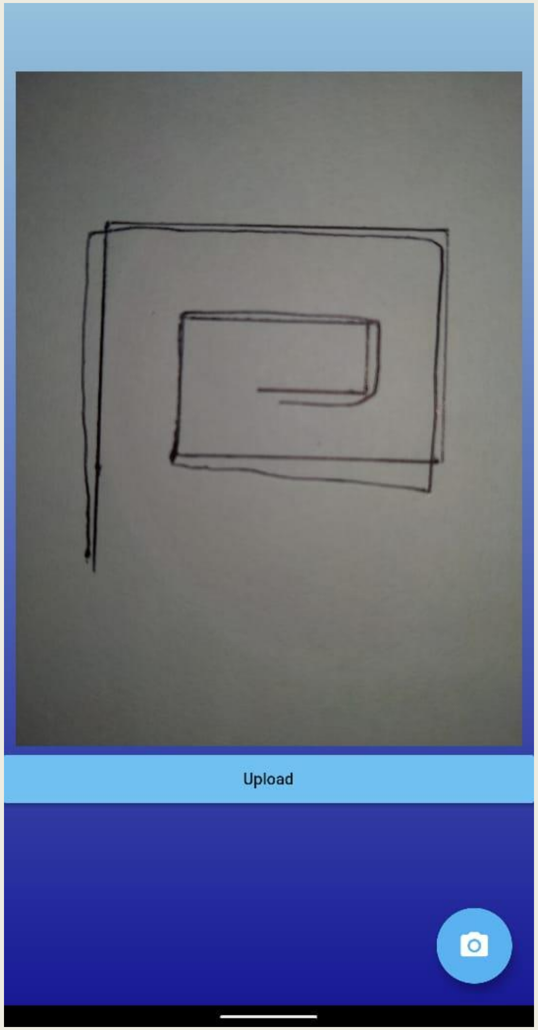
Three cursom layers added to VGG19 Architecture



Implementation (Trace Test)

MOBILE APPLICATION





Implementation (Speech Test)

DATASETS SURVEYED

Dataset	Accuracy	Size
PD dataset by Saker et al	73-85%	1040
Oxford Parkinson's Disease Detection Dataset	Upto 99%	200
Italian voice recordings	NA	850
MPower Database	Variable	65000+
Saarbruecken Voice Database	NA	NA

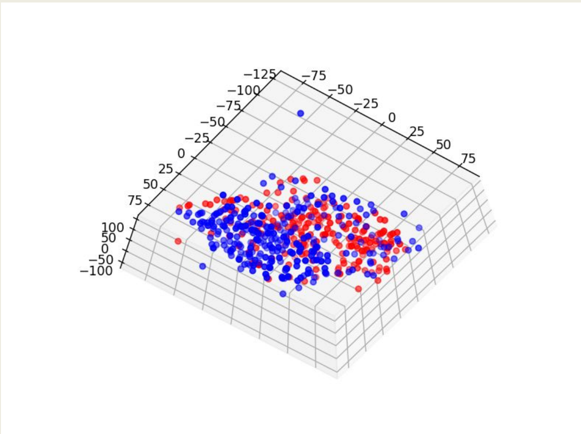
Implementation (Speech Test)

Baseline Work with Italian Dataset

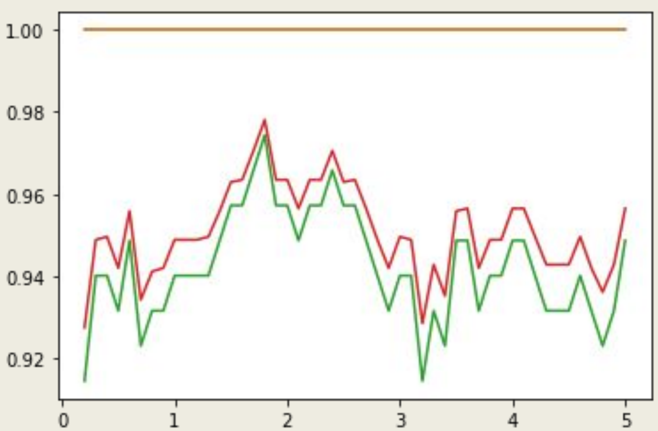
- Contains 800 recordings of both young and old people, split into three groups : elderly people with PD, young healthy controls, and old healthy controls
- Recordings saying various vowels, words and sentences.
- We considered only elderly people, both with PD and healthy controls
- Total of 585 resultant records, 220 controls and 365 with PD
- Converted into 26 acoustic features known to be good discriminators of PD patients from healthy controls

Implementation (Speech Test)

Spread of data points :



Variance of accuracy and F1-Score with weights :



Results and accuracy

Model	Accuracy	F1-Score
RF	97.4	97.8
XGBoost	94.3	95
NN	85	83
SVM	79	83

Best performing model : RF

Confusion matrix for Random-Forest:

```
[[47  1]
 [ 2 67]]
```

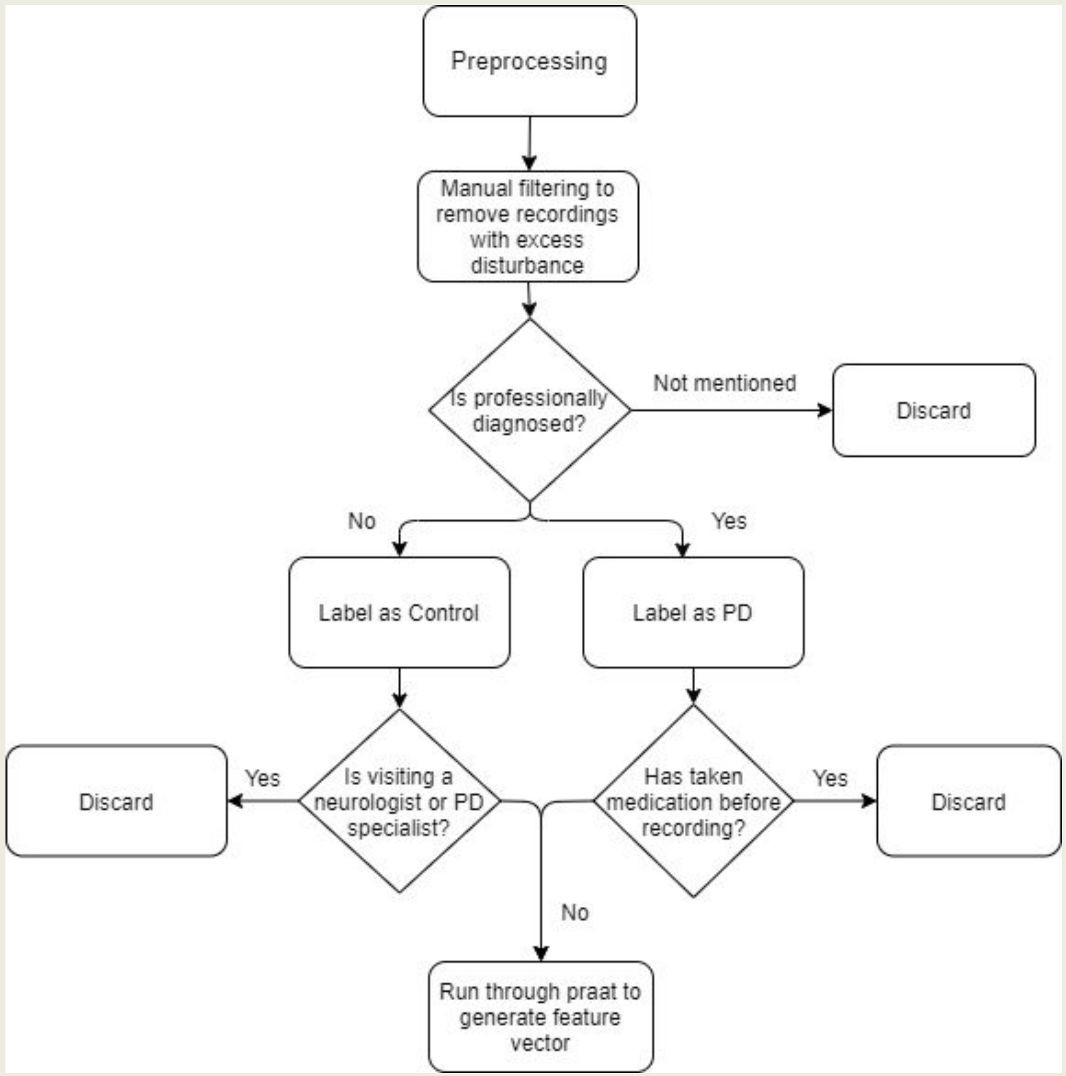
Implementation (Speech Test)

MPower DATASET

- Worked on the mPower Voice dataset, part of the mPower mobile Parkinson's Disease study which is by far the largest such dataset.
- Recordings containing the "aaa" sound for 10 seconds.
- Supplementary data
  - Time of medication
  - Healthcare provider
  - Year of diagnosis and onset of PD
  - Professional diagnosis

Implementation (Speech Test)

PREPROCESSING



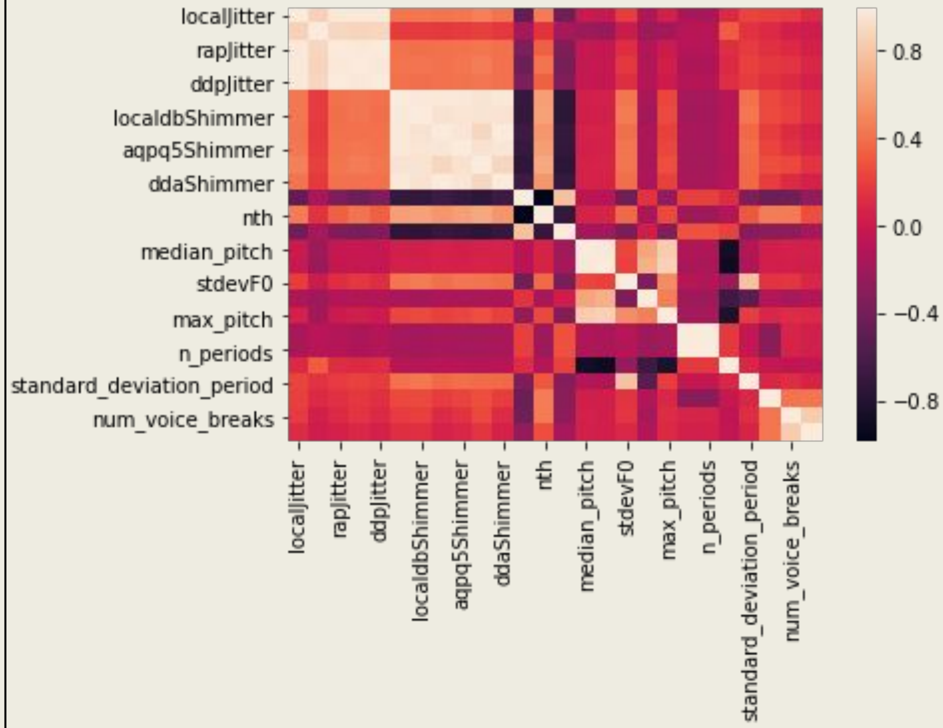
Implementation (Speech Test)

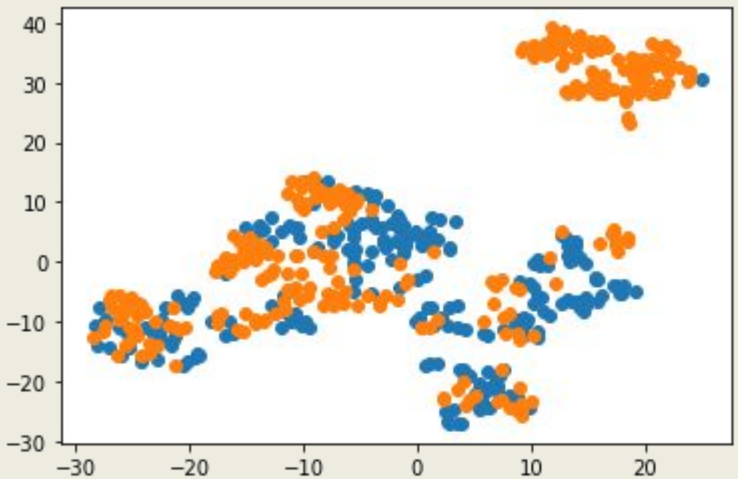
PREPROCESSING

- The recordings had to be converted to features for training the classifier.
- A Praat script was used to extract a total of 26 features from the voice samples.
- These 26 features have been proven as being successful for recognizing dysphonia and thus Parkinson's.
- The features include the Jitter, Shimmer, Pitch, Degree of Voice breaks and others.
- Praat-parselmouth; a python library for Praat, was used to extract the features from the data samples.

Implementation (Speech Test)

EDA PLOTS





Implementation (Speech Test)

SMOTE FOR IMBALANCE

- After preprocessing, the number of samples dropped to 2000.
- In these, 500 were records of PD Patients, and 1500 of healthy control.
- The dataset was now imbalanced.
- SMOTE is used for synthesizing new data points of the minority class from existing data, to overcome class imbalance.
- SMOTE works by drawing a line closest to the existing samples of the minority data class, and then generating new points around that line.

Implementation (Speech Test)

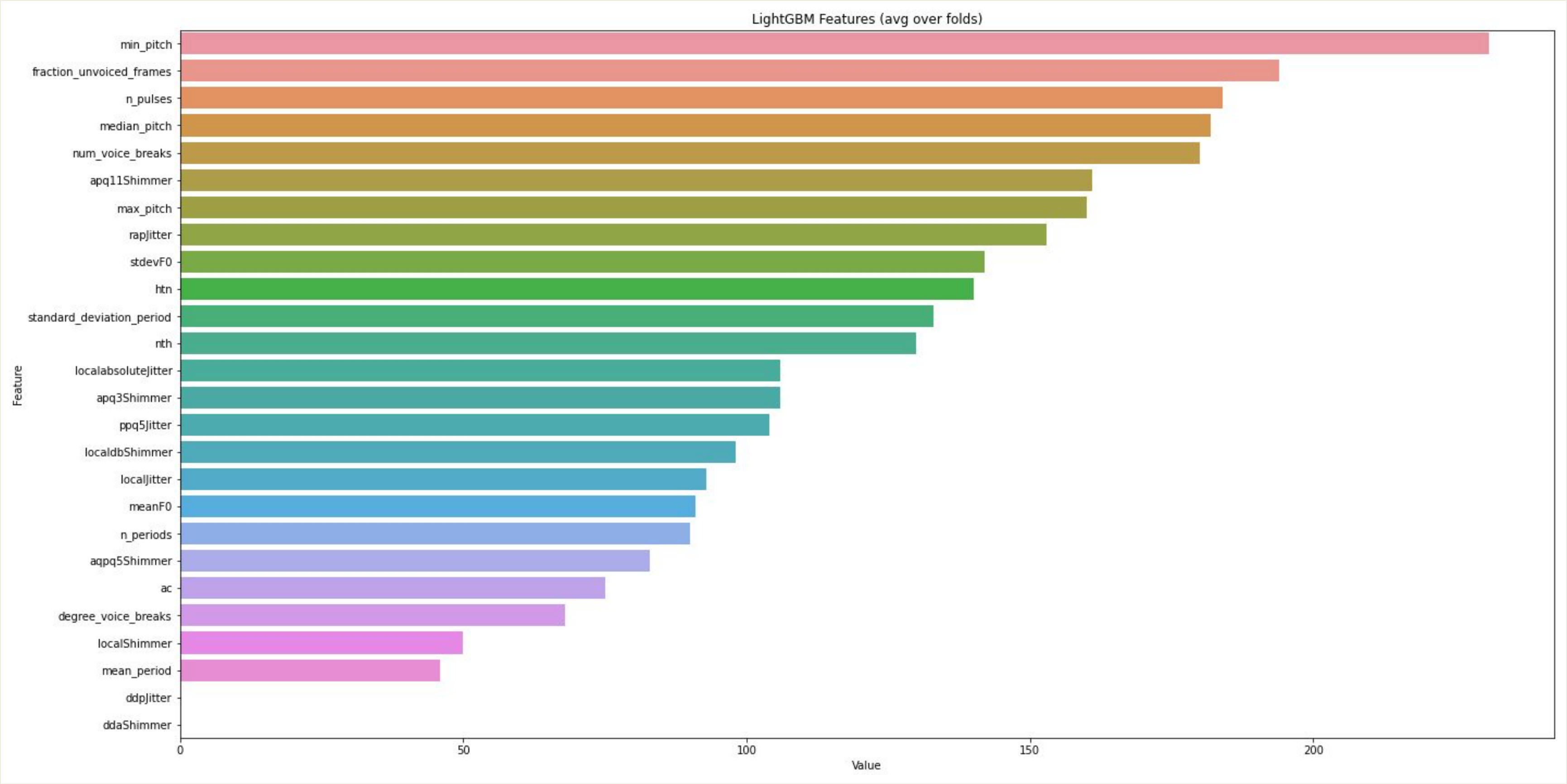
EXPERIMENTAL RESULTS

Model	Train	Test
Random Forest	100	90
SVM (Linear)	68	62
SVM (rbf)	62	55
SVM (sigmoid)	61	55
Naive Bayes	61	55
kNN	86	78
Decision Tree	100	79
XGBoost	90	71
LGBM	100	90
CatBoost	99	89

Implementation (Speech Test)

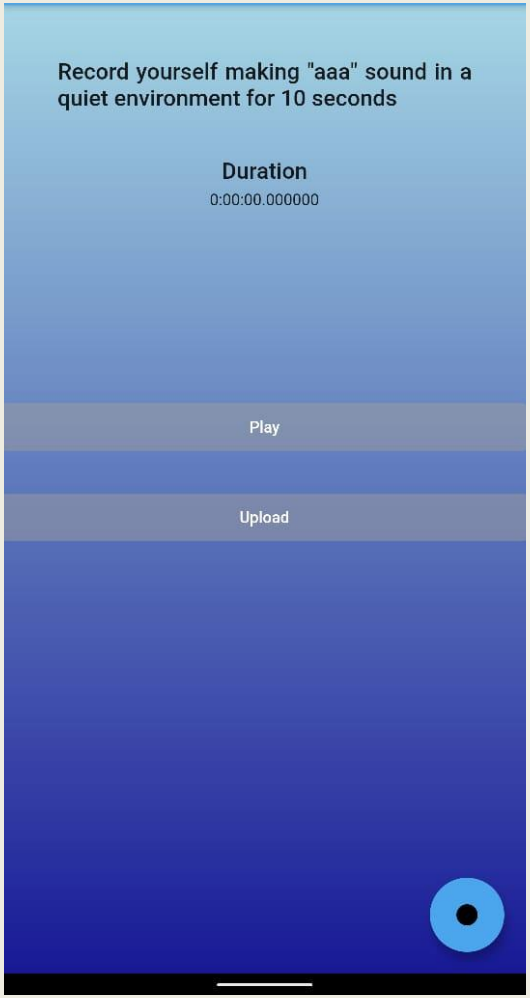
EXPERIMENTAL RESULTS

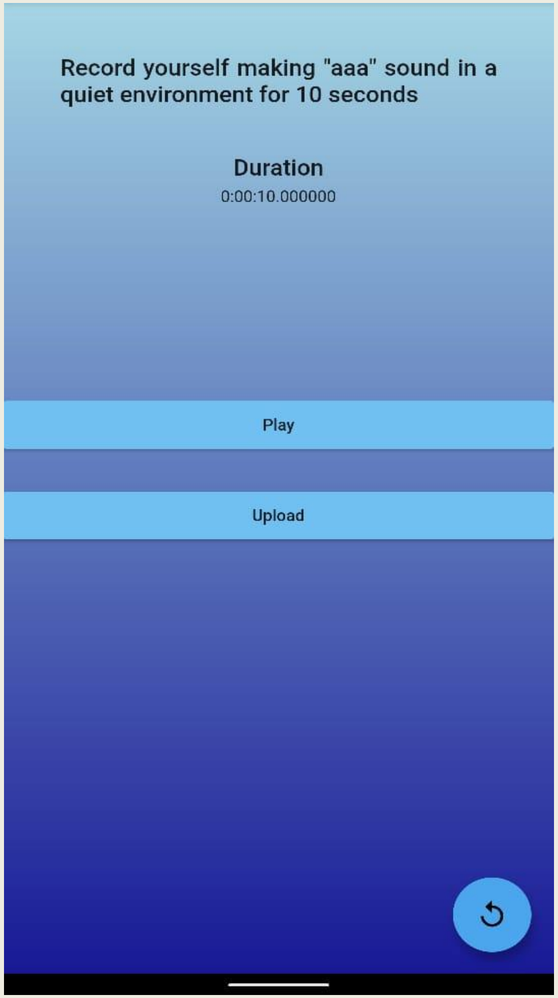
- Feature importance of the 26 features extracted



Implementation (Speech Test)

MOBILE APPLICATION





Implementation (Final Prediction)

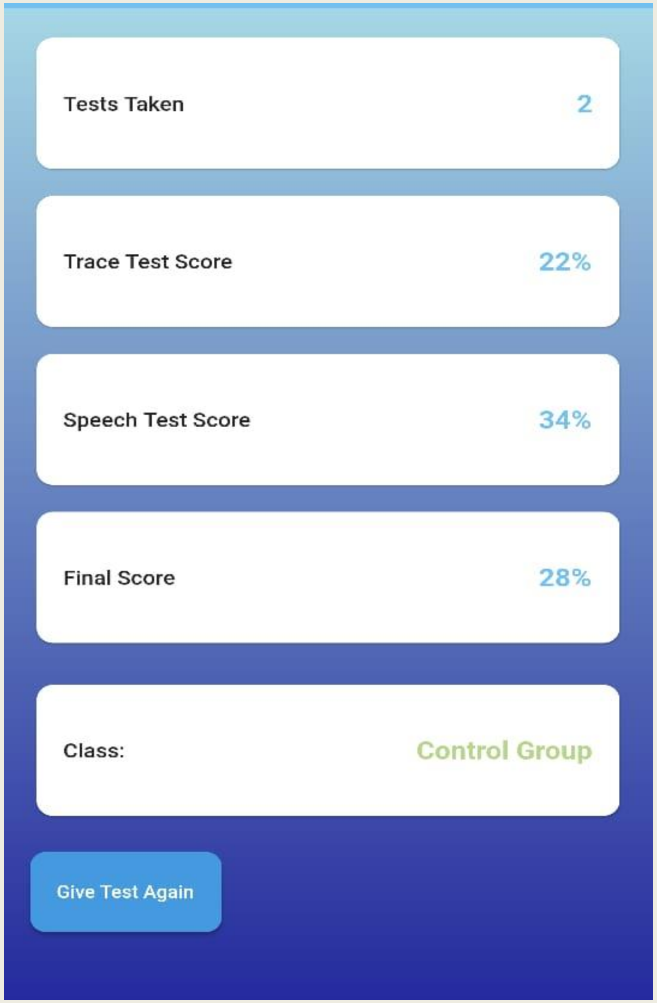
- A weighted average of the trace test and speech test prediction is calculated.
- $O_f = \Sigma A_i * O_i \,/\, \Sigma A_i$

Where

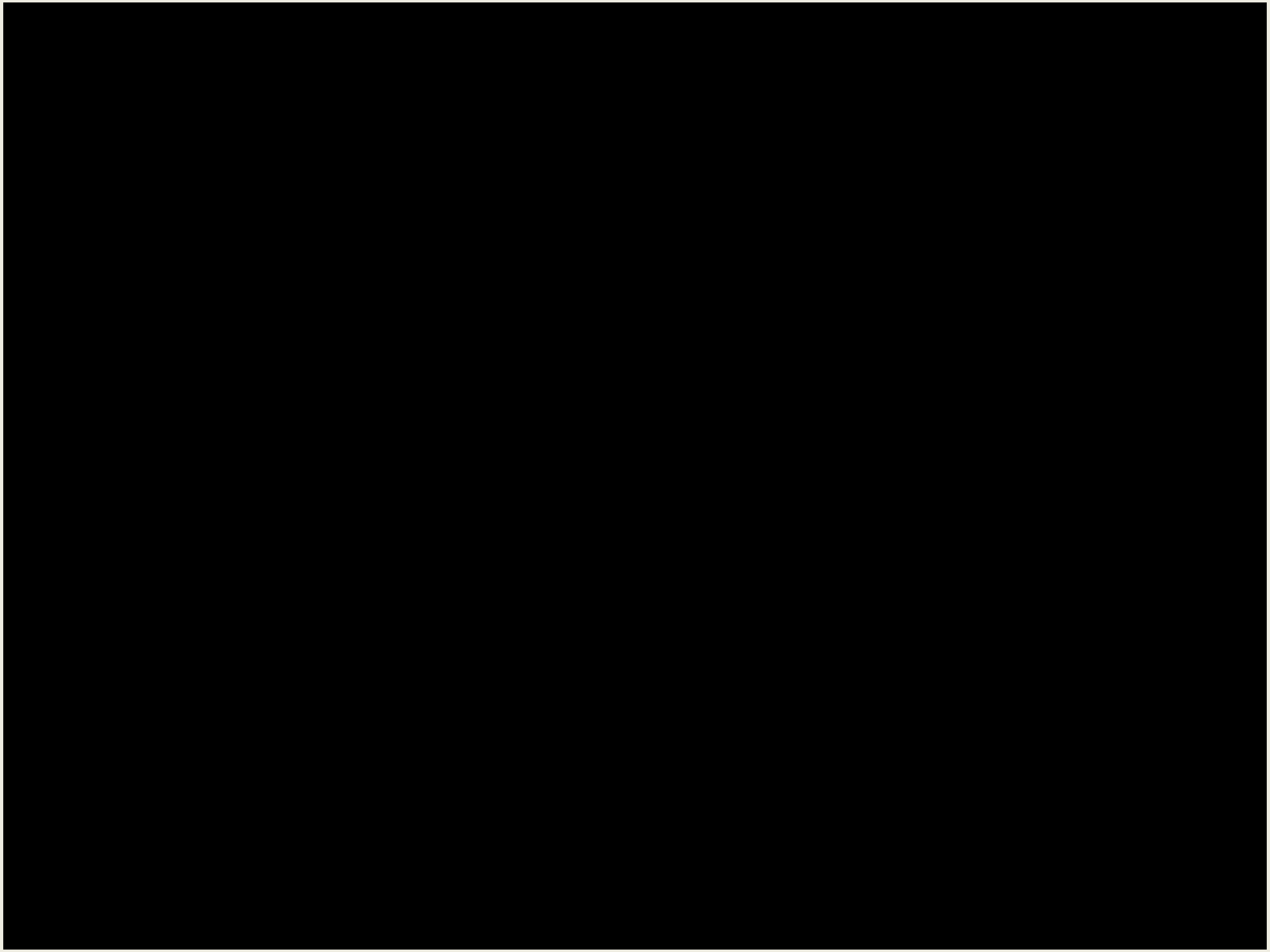
  - A_i is the accuracy of the i^{th} test
  - O_i is the output of the i^{th} test
  - O_f is the final weighted Output

Implementation (Final Prediction)

MOBILE APPLICATION

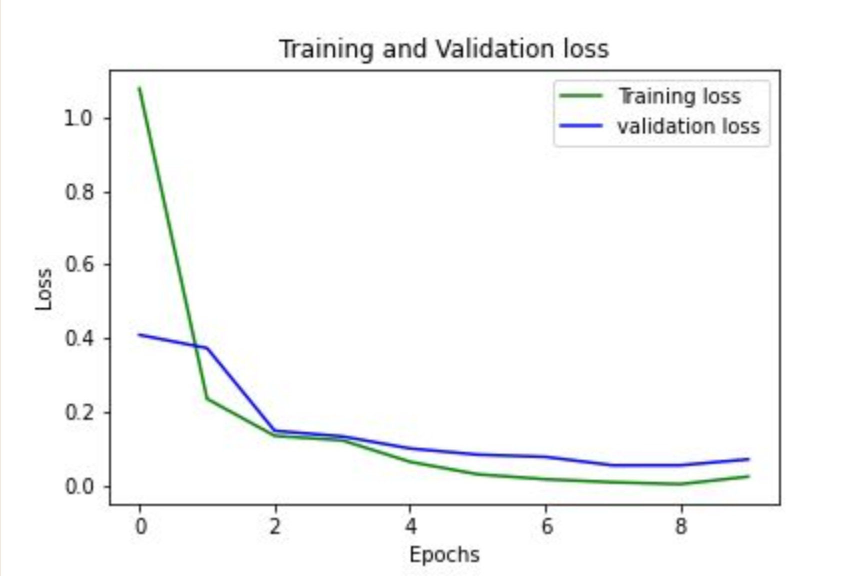


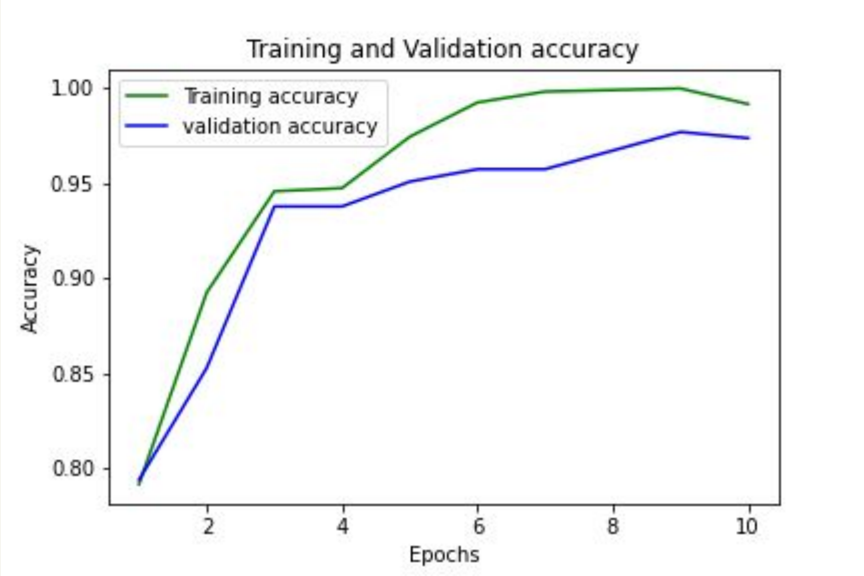
Demo Video



Results and Discussions (Trace Test)

- After augmentation, a total of 1526 images were generated.
- VGG19 Architecture gave the best accuracy on meander images.





Results and Discussions (Trace Test)

- Training accuracy - 99.18%
- Testing accuracy - 97.39%
- Time taken for training - 2 hrs 38 minutes
- FRR - 2.85% & FAR - 2.41%

```
array([[640,   0],
       [  0, 580]])
```

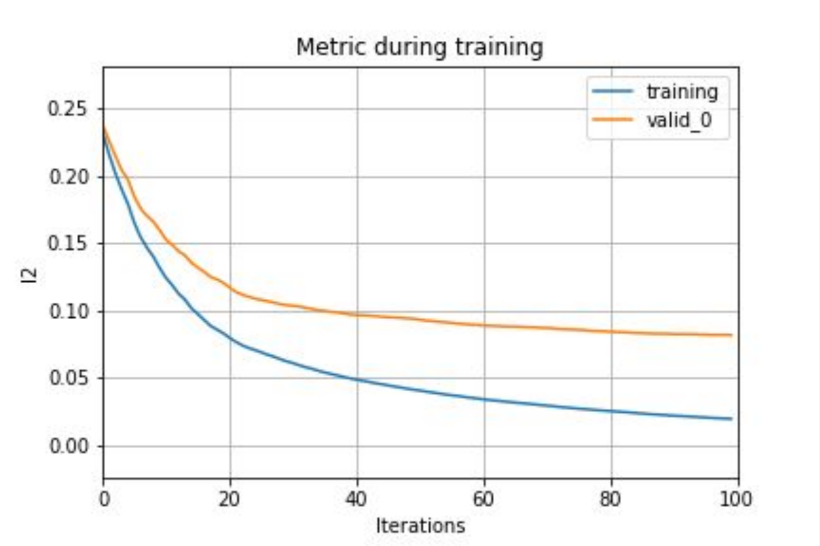
Confusion Matrix (Train)

```
array([[162,   4],
       [  4, 136]])
```

Confusion Matrix (Test)

Results and Discussions (Speech Test)

- 3000 samples were taken.
- After preprocessing, around 2000 samples remained.
- Control - 1517 , PD - 488
- Applied SMOTE
- LGBM gave the best accuracy



Results and Discussions (Speech Test)

- Time for training 0.375 seconds
- Training Accuracy - 100%
- Testing Accuracy - 91.21%
- FRR - 6.29% , FAR - 11.29%

```
[[1203    0]
 [   1 1205]]
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      1203
           1       1.00      1.00      1.00      1206

    accuracy                           1.00      2409
   macro avg       1.00      1.00      1.00      2409
weighted avg       1.00      1.00      1.00      2409
```

Train

```
Time:  0.375140905380249
[[267  34]
 [ 19 283]]
              precision    recall  f1-score   support

           0       0.93      0.89      0.91       301
           1       0.89      0.94      0.91       302

    accuracy                           0.91       603
   macro avg       0.91      0.91      0.91       603
weighted avg       0.91      0.91      0.91       603

0.912106135986733
```

Test

0 - Control

1 - PD

Conclusion

- Speech disorders and tremors are the most common symptoms observed among PD patients
- Thus, Speech and Tremor tests can help in early detection of the disease
- Commercial grade smartphones can be used for accurate PD symptoms analysis and detection
- Multiple tests give better validation

Future Scope

- More data can be acquired from the app to train the model
- Non motor symptoms can be tested as they generally develop before motor symptoms
- Data collected from the app can be used for training the models for both the tests with data from a single patient. This will also help in final combined accuracy judgement.

References

1. A. Naseer, M. Rani, S. Naz, M. I. Razzak, M. Imran, and G. Xu,“Refining parkinsons neurological disorder identification through deep transfer learning,”Neural Computing and Applications, 2020, 32 (3), pp. 839 - 854
2. Isenkul, Muhammed & Sakar, Betul & Kursun, O.. (2014). Improved Spiral Test Using Digitized Graphics Tablet for Monitoring Parkinson’s Disease. 10.13140/RG.2.1.1898.6005.
3. S. R. Sonu, V. Prakash, R. Ranjan and K. Saritha, "Prediction of Parkinson's disease using data mining," 2017 International Conference on Energy, Communication, Data Analytics and Soft Computing (ICECDS), Chennai, 2017, pp. 1082-1085, doi: 10.1109/ICECDS.2017.8389605.
4. Little, M & Mcsharry, Patrick & Moroz, Irene & Roberts, Stephen. (2006). Testing the assumptions of linear prediction analysis in normal vowels. The Journal of the Acoustical Society of America. 119. 549-58. 10.1121/1.2141266.
5. H. Zhang, C. Song, A. S. Rathore, M. Huang, Y. Zhang and W. Xu, "mHealth Technologies towards Parkinson's Disease Detection and Monitoring in Daily Life: A Comprehensive Review," in IEEE Reviews in Biomedical Engineering, doi: 10.1109/RBME.2020.2991813.
6. S. Arora, V. Venkataraman, A. Zhan, S. Donohue, K. Biglan, E. Dorsey,and M. Little, “Detecting and monitoring the symptoms of parkinson’s disease using smartphones: A pilot study,”Parkinsonism & related disorders, vol. 21, no. 6, pp. 650–653, 2015.
7. L. Ali, C. Zhu, N. A. Golilarz, A. Javeed, M. Zhou and Y. Liu, "Reliable Parkinson’s Disease Detection by Analyzing Handwritten Drawings: Construction of an Unbiased Cascaded Learning System Based on Feature Selection and Adaptive Boosting Model," in IEEE Access, vol. 7, pp. 116480-116489, 2019, doi: 10.1109/ACCESS.2019.2932037.

References

8. P. Khatamino, İ. Cantürk and L. Özyılmaz, "A Deep Learning-CNN Based System for Medical Diagnosis: An Application on Parkinson’s Disease Handwriting Drawings," 2018 6th International Conference on Control Engineering & Information Technology (CEIT), Istanbul, Turkey, 2018, pp. 1-6, doi: 10.1109/CEIT.2018.8751879.
9. H. Zhang, A. Wang, D. Li, and W. Xu, “Deepvoice: A voiceprint-based mobile health framework for parkinson’s disease identification,” inBiomedical & Health Informatics (BHI), 2018 IEEE EMBS InternationalConference on.IEEE, 2018, pp. 214–217.
10. Adams WR (2017) High-accuracy detection of early Parkinson's Disease using multiple characteristics of finger movement while typing. PLoS ONE 12(11): e0188226.
11. A. Agarwal, S. Chandrayan and S. S. Sahu, "Prediction of Parkinson's disease using speech signal with Extreme Learning Machine," 2016 International Conference on Electrical, Electronics, and Optimization Techniques (ICEEOT), Chennai, 2016, pp. 3776-3779, doi: 10.1109/ICEEOT.2016.7755419.
12. M. A. Little, P. E. McSharry, E. J. Hunter, J. Spielman, L. O. Ramiget al., “Suitability of dysphonia measurements for telemonitoring ofparkinson’s disease,”IEEE transactions on biomedical engineering,vol. 56, no. 4, pp. 1015–1022, 2009
13. Little, M.A., McSharry, P.E., Roberts, S.J. et al. Exploiting Nonlinear Recurrence and Fractal Scaling Properties for Voice Disorder Detection. BioMed Eng OnLine 6, 23 (2007)
14. P. Drotár, J. Mekyska, Z. Smékal, I. Rektorová, L. Masarová and M. Faundez-Zanuy, "Prediction potential of different handwriting tasks for diagnosis of Parkinson's," 2013 E-Health and Bioengineering Conference (EHB), Iasi, 2013, pp. 1-4, doi: 10.1109/EHB.2013.6707378
15. J. Mucha et al., "Advanced Parkinson's Disease Dysgraphia Analysis Based on Fractional Derivatives of Online Handwriting," 2018 10th International Congress on Ultra Modern Telecommunications and Control Systems and Workshops (ICUMT), Moscow, Russia, 2018, pp. 1-6, doi 10.1109/ICUMT.2018.8631265.

THANK YOU