Efficient Detection of Parkinson Disease Using Multiple Machine Learning Techniques

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Data Analytics

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Efficient Detection of Parkinson Disease Using Multiple Machine Learning Techniques

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Abstract

In the recent years there has been a significant surge in the diagnosis and monitoring of several diseases, out of which Parkinson disease (PD) is one of them which is commonly found in the elderly population. In this project we aim at developing a simplified and efficient screening method to diagnose PD benefiting medical practitioners who can screen the patients remotely. Currently, a series of spiral drawings are used as standard tests, different approaches are proposed that proves to provide better results compared to spiral drawings using the advanced Deep Neural Network models (Resnet 34, Resnet 50, Vgg19)in this project. Vgg19 outperforms Residual network models for spiral, wave and fusion based data. It is also observed that wave drawings are more insightful compared to spiral and fusion based data.

1 Introduction

Parkinson disease also known as Tremor and is caused due to the declination of the dopamine level in the brain which affects the motor functions, that is the physical functioning of a person. The neurons in the body of a person starts to die and are irreplaceable with increase in age of the person. The effects of the neurological conditions and the dropping of dopamine levels in patients body appear very slowly, hence it is hard to notice until the patients condition needs a medical attention. However, the symptoms and the levels of severity varies among different people. Some of the symptoms are voice impairment, loss of balance, unstable posture etc Shivangi et al. (2019).

According to WHO globally there are 10 million cases of confirmed PD each year. The risk of getting PD increases with respect to age, currently 4 percent of PD patients across the globe lie under the age of 50. It is estimated that 7 to 10 million are affected by PD every year worldwide.

1.1 Motivation and Background

The empirical approaches to address the PD are such as Unified Parkinsons Disease Rating Scale (UPDRS), the Parkinsons Disease Questionnaire 39, The Hoehn-Yahr Scale, and The Schwab and England Scale of Activities of Daily Living Goetz and Stebbins (2004). Among all the approaches UPDRS is most commonly used for the evaluation and to follow the progression of the PD in terms of surgical and medical interventions. The research for computer-based solutions in bio medical have improved the decision making considerably over the last few years. Many studies have proved that there exists a correlation between the speech disorders and PD. Also, many studies have reviewed that 90% of the patients exhibit the vocal impairment and speech problems at the early stage of PD. Hence, the samples of speech from the patients would be ideal in terms of the decision support system that helps in building PD diagnostic tools based on vocal features. From recent studies computer-based solutions research have led to the discovery of some machine learning methods which makes use of the audio recordings that are associated with the PD. This study aims at measuring the dysphonia which is mostly observed in the audio samples of PD patients.

Lately, it has been proved that the with the help of modern imaging techniques, the genetic and biological biomarkers would help in bringing considerably high accuracy to support decision making in the PD diagnostic tools. In 2017 by a group of Australian researchers a new methodology to diagnose PD was discovered where the spiral drawings drawn by PD patients were used. This technique analysed the amount of time, the pressure exerted and the characteristics of the lines to determine the signs of PD.

There exist various applications in the market for screening Parkinson patients, where some applications make use of the speech and rest tracks the PD based on the chronic conditions of the patients which can be easily detected using the sensors such as accelerometer and gyroscope which are very common in smartphones. Previously there has been a very limited amount of research work done on Parkinson detection by making use of the Vocal and the characteristics of Spiral drawings. The main goal is to propose an efficient and simplified method for detection of Parkinson remotely reducing the consulting cost. By creating a model that detects the PD affected patients using the advanced Image classification algorithms which helps medical practitioners screen the patient remotely and accurately with very less time and cost. It will also be beneficial for patients for early detection of PD and take necessary medical consultation.

1.2 Project Requirement Specification

This phase emphasizes on developing a computer vision model for screening and detection of PD using the spiral and wave tests from the patients. This application would benefit medical practitioners to screen efficiently at very low cost as well as to the patients to seek the medical attention they need. The research question and objectives are as follows.

1.2.1 Research Question

RQ: "*How can detection of Parkinson can be improved using the spiral and wave sketches of Parkinson patients, using multiple machine learning techniques (deep neural networks i.e. Resnet 34 and Resnet 50), visual geometry group-19 (Vgg19) and random forest for effective diagnosis of Parkinson to support medical practitioners to ameliorate the screening and save lifes of people*?" Multiple neural network models are implemented and the accuracy is compared and tested for detection of Parkinson disease.

1.2.2 Research Project Objectives and Contribution

A set of objectives are derived and executed in this project to address the above mentioned research question as shown in Table 1. The mentioned objectives cover the critical review on the data-set and the existing methods of Parkinson detection, Data pre-processing, the implementation of innovative techniques for Parkinson detection through wave and spiral sketches and the comparison of the developed models also with the existing models.

Table 1: The research objectives for this project are as follows:

Obj	Objectives and Contributions	Method	Metrics
1	A critical literature review on the Parkinson detection		
2	Data preparation using the raw images		
(2.1)	Resizing of the images to a particular size for analysis.		
3	Implementation and evaluation of the machine learning models	Spiral,	
(3.1)	Implementation, Evaluation, Results Resnet 34 model	Wave,	Accuracy,
(3.2)	Implementation, Evaluation, Results Resnet 50 model	Fusion	Sensitivity,
(3.3)	Implementation, Evaluation, Results Vgg19 model		Specificity
4	Identifying the Parkinson disease from spiral and wave data-set		
5	Comparison of developed models (objective 3)		
6	Comparison of developed models verses existing models		

The technical report is framed as follows; Section 2 represent the literature review of empirical analysis of Parkinson disease within medical industry from 1998 to 2019. Section 3 introduces the Parkinson methodology used in this project, section 4 presents the design specification, section 5 presents the implementation, section 6 presents the evaluation and the results are tabulated that are obtained from the machine learning algorithms. Finally, the section 7 concludes the research project with the obtained results and the future work that can overcome the limitations of this project.

2 Related Work

2.1 Introduction

In the recent years health informatics have gained a wide popularity for detecting and monitoring of several important diseases. One of the very important disease is Parkinson which is commonly seen in people over 60 years of age, this can be monitored and detected using the information system that are based on the artificial learning using the real information from the patients. Many studies have indicated that the Parkinson disease is directly associated with the motor functioning disorder symptoms, such as rigidity, tremor bradykinesia etc. Rigidity and bradykinesia always are seen in the early stages of the PD which affects the writing and sketching ability of the of the patients, from studies it is found that the handwriting of a person is influenced by several factors such as education, knowledge and language proficiency (Zham et al.; 2017). Whereas the sketching of spiral and wave drawings are independent and non-invasive measures. Obtaining the features from the handwritten sketches will be dynamic and help in real-time and reliable analysis, also will be able to develop applications that can extract these features through an online assessment of the patients.

2.2 Current State of the Art for PD Diagnosis

The most commonly used state of the art method for diagnosis of PD by medical practitioners, under clinical environment is by observing and judging of patients from their medical history and assigning a scale of rating based on patients performance. The most commonly used rating till today is the Unified PD rating Scale (UPDRS) Goetz and Stebbins (2004). Getting to know the Severity level of the PD is vital and optimal clinical decision. Recent advances have lead to the usage of spiral drawings, enabling clinically to study the severity level of PD which is associated with the movement disorder by continuous monitoring. It is evaluated from the features extracted from the writing speed and the tremor subjectively. The researchers found that the indices of severity level, first order zero crossing, second order smoothness and the mean speed of the spiral test were corelated with the Unified Parkinson Disease Rating Scale III (UPDRS) score (Saunders-Pullman et al.; 2008).

The guided Archimedean spiral drawings drew by the PD patients, the Composite Index of Speed and Pen-Pressure (CISP) were computed and analysed and was found that there exists a correlation between the speed, pen-pressure with respect to the severity of the disease (Zham et al.; 2017). The previous studies indicate that the technological advancements would benefit in assessing the PD symptoms more accurately than ever before by identifying the disruption in the motor movements that are associated with the PD?. Researchers have proposed numerous machine learning techniques where it was found that audio recordings associated with PD benefited in assessing the PD symptoms Little et al. (2007). The study aimed at analyzing the defects in the voice which was found mostly among the PD affected people, where sound recordings from 31 patients were recorded spelling "a" vowel reducing the defective voice feature from the recordings it was able to identify the severity of the disease and attempts were made to analyze remotely.

2.3 Impact of Spiral Analysis and Computation

Using spiral drawing in the analysis of ascertain PD cases is relatively new in the area of medical science. Spiral drawings are considered as a standard approach to test the severity of tremor for clinical evaluation of medical treatments. Initially tremor severity was analysed and estimated visually by the movement disorder experts, later this approach was replaced by the mathematical signal analysis capturing the kinematic, dynamic and the spatial abnormalities. These results helped to capture indices that determined and estimated the motor performance and the disability. Different types of cases and controls were compared and contrasted based on the age, gender and the tendency of the use of hand in the linear mixed effect models (Legrand et al.; 2017).
Wang et al. Proposed a new quantitative evaluation method that is based on varying the origin based on the polar coordinate system, which used the characteristic parameters extracted from the hand movement of patients with PD during the spiral test. These values were linearly interpolated which helped to capture good predictors of PD. Results achieved using spiral drawings have provided significant evidence that it yields optimal accuracy for early diagnosis of PD.

2.4 Critical Review on Methods Employed for PD Diagnosis

Over the years several researches that were aimed at providing solution to the PD diagnosis, expert systems based on machine learning techniques have proven to provide better results. Analysis performed on signal processing from the voice of PD patients is widely encountered in most part of the works that measures dysphonia (Sakar et al.;

2013). Another approach for diagnosing PD is Micrography, handwritten exams written by PD patients is used measure and characterize the disease, since the PD patients exhibit the feature of hand tremor that affects the writing skills. In recent days the handwritten forms filled out by PD patients are used in the process (Little et al.; 2007).

Automatic recognition of the PD was possible with pattern recognition techniques.Spadoto et al. made use of the Optimum-Path Forest classifier technique. Artificial Neural Networks with Multi-Layer Perceptron (ANN-MLP) was introduced to diagnose and evaluate the effects of PD. Later the performance of ANN-MLP, Support Vector Machines (SVM), Neural Networks with Radial Basis Functions techniques were used to measure the effect of tremor on PD Patients(Panicker et al.; 2013). .

Optimization of parameters and the extraction of the features were performed simultaneously, in a computer-oriented system that used Fuzzy K- Nearest Neighbors classifier and Particle Swarm Optimization techniques. These techniques aided to the diagnosis of PD achieving an accuracy of 97.4%. For identification of Pd an Hybrid Method was implemented which used the Extreme Learning and subtractive Clustering Features Weighting technique. This Hybrid method helped in achieving a sensitivity and accuracy of 99.49% and 100%. Ma et al.made use of same data-set and both were able to achieve a significant result. The identified gap in both of the work was that data was comprised with 74% of PD patients, where we can see that the results might be biased.

Introduced a system that uses the Magnetic Resonance Images (MRI) for diagnosing PD. The system made use of brain images, where valuable insights were achieved based on the thought that there is a connection between different regions of the brain. This method was used to diagnose PD patients assuming that the region of brain may have strongly affected, and the differences can be marked visually. Even though this process yielded good results and was a first in class work as until then all the other diagnosis methods was completely based on signal-based features, it becomes very expensive to obtain MRI images and involves a lot more complications as the patients have to stand still during the image acquisition process which is not straightforward for PD patients(Haller et al; 2013). Both spirals and meanders filled out in forms by PD patients were compared with a template for feature extraction using the advanced computer-vision and machine learning techniques. The system was able to achieve higher results with meander images compared to spiral images. An accuracy of 67/% was achieved using this technique. The data that is used comprises 80.44% of PD patients and 19.56% of control individuals which would bias the result (Pereira et al.; 2016). In Sweden a study was conducted combining the spirograph data of 30000 and clinical assessment of 65 advanced PD patients where the animated spiral measurements was observed and visualized. The researchers made use of machine learning algorithms such as random forest, support vector machine, logistic regression and other classification models that aimed at distinguishing PD patients from the state of bradykinesia and the state dyskinesia. This experiment was also focused on visualizing the spirals to understand which part of the spiral drawings would help clinicians make better decisions, from the study we identified that the clinicians did significant error in classifying the PD patients. Hence this technique is not so beneficial after all as it increases the chance of human error. Also, we identified from the result obtained from confusion matrix that a lot of cases are misclassified Sadikov et al..

2.5 Comparison of Reviewed Methods Employed for PD Diagnosis

Based on the aforementioned literature review multiple methodologies and the techniques used by previous researchers with respect to the data-set used, we have tabulated the results and the methods from previous studies to detect Parkinson. We mainly consider the Deep Neural Network image processing technique for comparison and modified SVM employed by Pereira et al. (2016). who achieved 67% on the spiral and meander images. Spadoto et al. (2010). achieved 73.53% accuracy for KNN method and 67.84% for ANN + MLP method using voice signal processing for detection of Parkinson. Optimised Cuttle Fish techniques was used by Gupta et al. (2018) to improvise the diagnosis of PD achieving a result of 88%. Many researchers have used speech signals Sakar et al. (2013) Little et al. (2007) (Zuo et al.; 2013) albeit the results achieved are high from using the speech signals recorded under clinical environment it is alone not suitable for remote diagnosis of PD.

Table 2: Parameters generated from features

Method	**Accuracy**	**Data**	**Author**
SVM	67	Meander Sketches	Pereira et al. (2016)
NB	78.9	Meander Sketches	Pereira et al. (2016)
SVM Classification	82.57	Audio Recording	Sakar et al. (2013)
OCFA	88	Meander Sketches	Gupta et al. (2018)
KNN Classification	78.57	Audio Recording	Sakar et al. (2013)
KNN	73.53	Spiral Sketches	Spadoto et al. (2010)
ANN + MLP	67.84	Spiral sketches	Spadoto et al. (2010)
PSO-FKNN	97.40	Audio Recording	Zuo et al. (2013)
Preselection filter+ SVM	91.40	Audio Recording	Little et al. (2007)

2.6 Conclusion

From the literature review we can conclude that there is a major gap and scope for development of advanced image processing models by fine tuning the computer vision based algorithms to ease the detection and screening of Parkinson, benefiting the medical practitioners/specialists making use of the spiral and wave images drawn by the PD patients. In the next chapter we discuss the scientific methodology and the architectural design of the project.

3 Parkinson Methodology Approach and Design Specification

3.1 Introduction

One should know how to make use of the data by understanding the business needs and the stakeholders as the data mining is important element in this methodology. We are following modified CRISP DM methodology in this study as we try to understand the image patterns of spiral and wave drawings drawn by PD patients to detect Parkinson. In the following section we discuss how we are achieving the research objectives with our modified CRISP DM methodology and architectural design.

3.2 Modified Methodology for Detection of Parkinson Disease Using Spiral and Wave Images

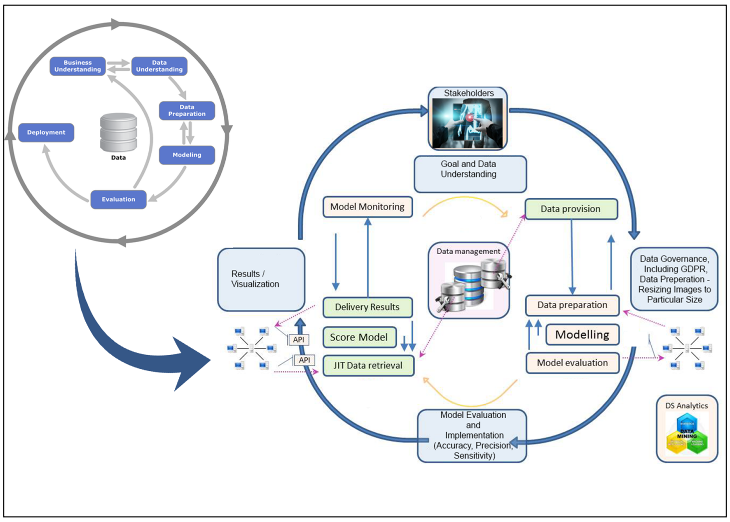

Figure 1: Modified Parkinson Methodology

Goal and Data Understanding: This stage is addressed to the project objectives of this research project. The main goal of this project is to quantify the visual appearance of the drawings classifying Parkinson vs healthy and build a deep neural network model to classify them.

Data Governance and Preparation: Based on the objective of this research the data is searched, that is ethical to use for research work as per the GDPR is downloaded from NIATS of Federal University of Uberlndia. The data consists of raw images of spiral and wave drawings which will be resized to the particular size using which knowledge can be extracted.

Model Evaluation and Implementation: Multiple machine learning models are implemented and tested through spiral and wave data-set to detect Parkinson disease quantifying the visual appearance. Accuracy, sensitivity and specificity of the models are used as primary metrics for evaluation of test results.

Results and Visualization: The obtained results are compared with the research objectives that are described in the beginning of this research project and conclude the project.

3.3 Three Tier Architecture Design Specification

In this research project of classifying Parkinson vs healthy using the spiral and wave drawings we make use of the three-tier architecture. First tier is the data persistent layer which consists of transforming raw data into usable format which can be used to extract knowledge and the data is split into test and train data. Second tier is the business logic tier that consists of different machine learning techniques and are applied and tested on the models. The third tier is the last tier that is the user/client layer, in this tier the raw images are provided as input and the obtained results are visualized and tabulated for end user.

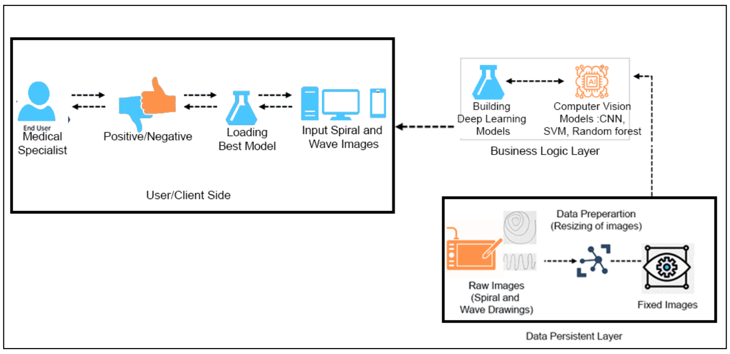

Figure 2: Design Specification

3.4 Data Pre-processing

We are using the spiral and wave dataset obtained from NIATS of Federal University of Uberlndia. The dataset consists of 204 spiral and wave images. The obtained images are of two types, one is Parkinson and the other one is healthy images. The data set is already labelled as healthy, Parkinson, spiral and wave as shown in fig3. In this step we perform resizing of all the images to one size that is 128*128 as deep learning models can only be applied on the images of the same size. After running the test we discover that the models were not able to explore the pixels from from the 128*128 image bunch, hence the image bunch are recreated with 256*256. In our research we split 72 training and 30 testing images from 102 spiral images, also the wave images are split in to 72 training and 30 testing images.

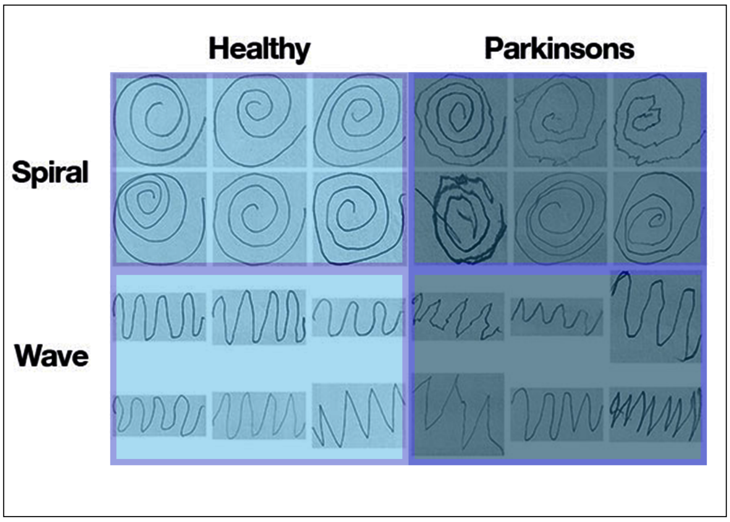

Figure 3: Spiral and Wave Dataset

3.5 Conclusion

In this research project we have adapted the CRISP DM methodology and we make use of the modified CRISP DM in this project. The architectural and scientific design describes how the objectives are achieved in this project for the researchers to understand. Also, the data pre-processing and the implementation is described in this section. In the next chapter we will be describing more about the implementation and design specifics of the project

4 Implementation for Parkinson Detection

4.1 Introduction

The implementation is described in this section for Parkinson detection through spiral and wave drawing data-set that was pre-processed in the previous section. The data is split into testing and training in the 80% and 20% ratio, moving forward making use of different machine learning methodologies such as computer vision and fastai associated with different deep learning models is discussed in the following section. The libraries that are employed and the parameters considered to build the models for the test and training data are discussed in the implementation section. The performance of the models are compared and is discussed in detail based on the parameters considered. The project is implemented making use of python as the primary programming language, computer vision and Fastai are used for evaluation of models performance, libraries as in Numpy for numerical analysis and matplotlib to plot learning curves and validation of data are used in this project. The aforementioned objectives are discussed in detail in this section.

4.2 Implementation using Fastai Library and Residual Networks Models

In this project we make use of the Fastai library that is built upon PyTorch, providing a single interface to the most commonly used applications such as vision, time series, tabular data and more. We make use of Tesla T4 gpus in this research project.
The project is based on the following dependencies
1. Google Colab which helps us in GPU usage
2. Fastai
3. PyTorch v1

Deep convolutional neural networks have given rise to many breakthroughs in image classification. In recent days Resnet have gained popularity for image classification which is indicated with the number of layers in the end it equates. The main problem implementing Resnet would resolve in image classification is vanishing gradient problem with batch normalization. In case of computer vision data-set, we need to convert data into the DataBunch object ImageDataBunch in this project. Image augmentation is performed with the help of Fastai on test, train and validation data which helped us resolve the regularization problem.

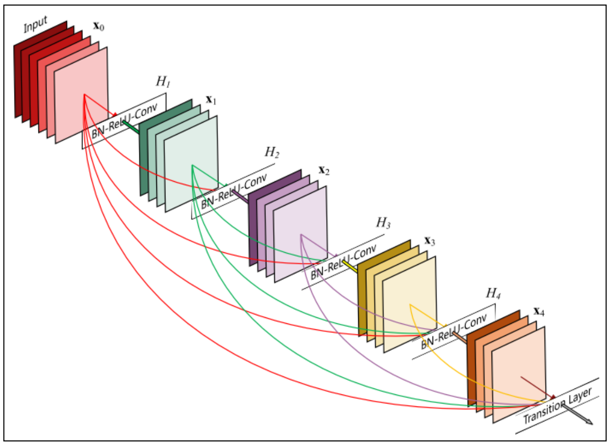

Figure 4: Overview of Resnet

In this project we try to test and compare the accuracy of the models for spiral, wave and mixed drawings. The data is split and the images are re-scaled in to '128*128' and '256*256' different sizes and batch size '8'. The class mode in this project is 'categorical' that helps in encoding class labels 'Parkinson' and 'Healthy'. The figure below shows the output of the image augmentation.

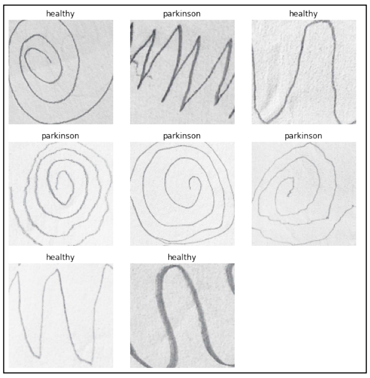

Figure 5: Image Augmentation Output

The Residual network is initialized by the following parameters
1. 128*128 and 256*256 size images
2. Two image types ('Parkinson' and 'Healthy')
3. Accuracy as metrics

4.3 Implementation for Parkinson classification in spiral drawings using Vgg19

Vgg19 is a deep (convolutional) neural network model that made of 19 deep layers. Originally it is a pre trained classification model built to classify images into 1000 object categories on more than a million images from ImageNet database Simonyan and Zisserman (2014). As shown in Figure 6, Vgg19 consists of 5 convolutional layers where each layer has sub layers in it which is a total of 16 and 4 max-pooling layers. Layers FC1, FC2 and softmax helps in storing all the features extracted from the images.

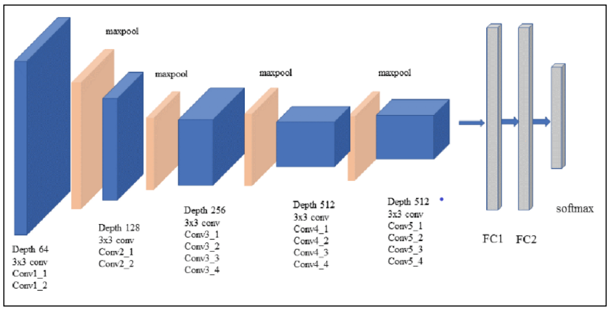

Figure 6: Vgg19 Overview

In this project we make use of a pre trained Vgg19 model, we would not be using the FC1, Fc2 and softmax layers, Albeit we will be using these layers to classify the drawings into 'Parkinson' and 'healthy'. We will only focus on convolutional layers and make sure no weights are changed and remains same while running multiple epochs.

5 Evaluation and Results

5.1 Introduction

In this section we discuss the Evaluation and the results achieved for Parkinson detection. The models performance is tested and evaluated based on the Accuracy, Precision, Recall. (Tharwat,2018).[1]

1. Accuracy: The images classified correctly divided by the total number of the images from the data-set.

$$\text{Accuracy} = \frac{Correctly\ classified\ images}{Images\ in\ the\ dataset}$$

2. Precision: To identify and measure the correct positive values we consider of using precision metrics .

$$\text{Precision} = \frac{true\ positives}{true\ positives + false\ positives}$$

3.Recall: It is the number of correct positive esults divided by the number of all relevant samples (all samples that should have been identified as positive).

$$\text{Recall} = \frac{true\ positives}{true\ positives + false\ negatives}$$

5.2 Case Study 1: Evaluation and Results for Spiral Drawings

5.2.1 Resnet 34

In this project Resnet 34 when applied for spiral based data an accuracy of 83.33% is achieved with the sensitivity of 73% and 93% specificity as shown in the table below. Figure 8 represents the graph for train loss and confusion matrix for Resnet 34. When the model was trained on the images with size 128*128 the train loss was higher than the

[1] Evaluation Metrics: https://towardsdatascience.com/metrics-to-evaluate-your-machine-learning-algori

validation loss which indicates the under-fit in the model, hence we increased the size of the images to 256*256 from this the confusion was reduced in the model and the under-fit problem was resolved. By the results we can conclude that it is not a great model, as the sensitivity achieved is low.

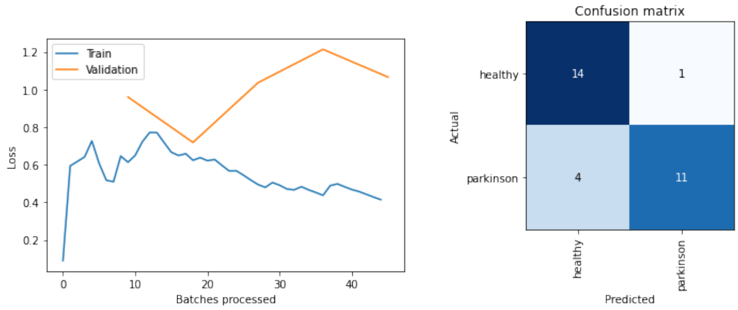

Figure 7: Resnet 34 Train Loss and Confusion Matrix

5.2.2 Resnet 50

Many believe that increasing the layers in neural network thus increases the performance of the model, hence Resnet 50 model was given a try in this project. The results achieved is tabulated in the below table and it is observed that the accuracy of the model remains same as Resnet 34 that is 83.33%, albeit the sensitivity has significantly increased compared to the Resnet 34 that is 86%, which is a very good sign for this project as sensitivity is vital in medical diagnosis and specificity of 80% is achieved. The confusion matrix from figure 9 shows that 11 cases have Parkinson out of 15 cases from only spiral data that is correctly identified by the model.

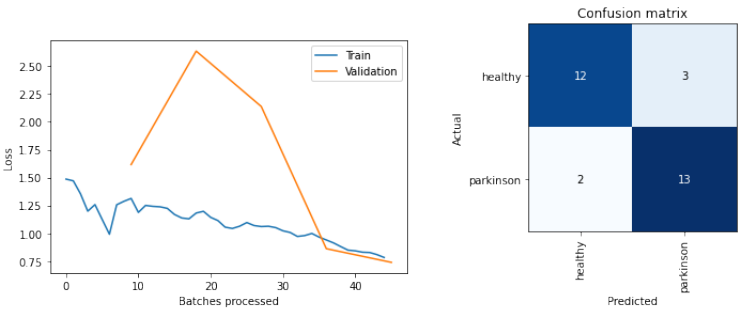

Figure 8: Resnet 50 Train Loss and Confusion Matrix

5.2.3 Vgg19

Vgg19 in this case when applied on only spiral based data, it provides a result of 80% in terms of accuracy, specificity and sensitivity. Figure 10 shows the train loss graph and the confusion matrix. The confusion matrix shows 12 cases of total 15 cases are correctly identified for both Parkinson and healthy for spiral data.

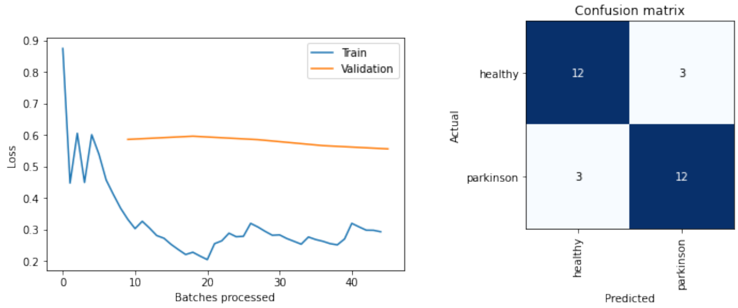

Figure 9: Vgg19 Train Loss and Confusion Matrix

Table 3: Accuracy of the models for Spiral data

Method	Accuracy(%)	Sensitivity(%)	Specificity(%)
Resnet 34	83.33	73	93
Resnet 50	83	86	80
Vgg19	80	80	80

5.3 Case Study 2: Evaluation and Results for Wave Drawings

5.3.1 Resnet 34

In this project Resnet 34 is applied on wave based data and ran 5 epoch cycles, the model is run on both 128*128 and 256*256 size images and found that 256*256 yield better result. 86.66% of accuracy, 86.66% of sensitivity and 86.66% of specificity is achieved as tabulated in table 2. The figure 13 represents the train loss over validation loss and shows the confusion matrix, 13 out of 15 cases are correctly identified as Parkinson positive cases. By observing the achieved results the model performs well on wave based data.

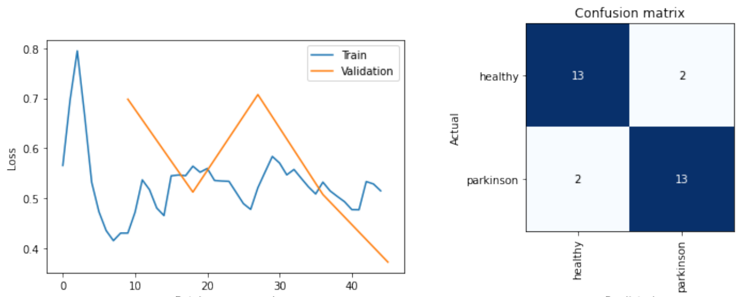

Figure 10: Resnet 34 Train Loss and Confusion Matrix

5.3.2 Resnet 50

Resnet 50 is applied on the wave data and found no improvement in the result compared to Resnet 34. An accuracy of 73%. Resnet 50 model does not yield good results on wave based data. The figure 11 represents the train loss and the confusion matrix produced for Resnet 50 model for wave data.

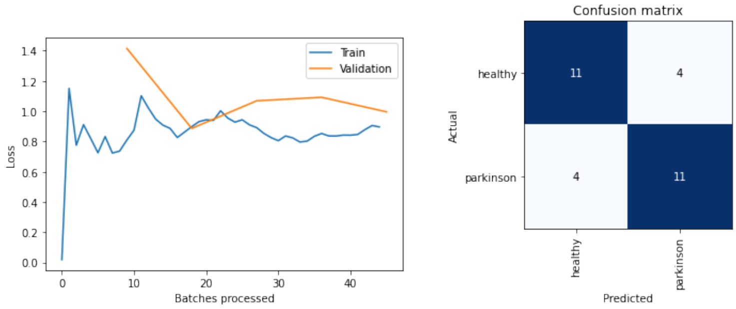

Figure 11: Resnet 50 Train Loss and Confusion Matrix

5.3.3 Vgg19

Sensitivity is very vital in our project as discussed earlier and Vgg19 provided 93% sensitivity and 90% accuracy when run on wave only data. From the figure 12 we can notice that 14 out of 15 cases are correctly identified using Vgg19 model. Vgg19 model performs very well when applied on wave based data. We have also achieved a high sensitivity for wave data, as in this project we aim at achieving higher sensitivity.

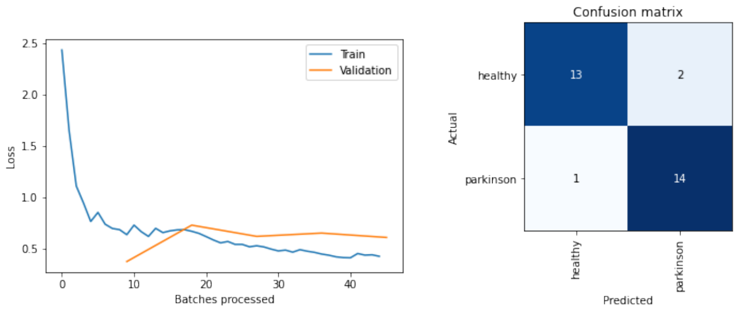

Figure 12: Vgg19 Train Loss and Confusion Matrix

Table 4: Accuracy of the models for Wave data

Method	**Accuracy(%)**	**Sensitivity(%)**	**Specificity(%)**
Resnet 34	83.33	83.33	83.33
Resnet 50	73	73	73
Vgg19	90	93	80

5.4 Case Study 3: Comparison of Models Performance for Wave and Spiral Drawings

5.4.1 Resnet 34

The model obtained 85% accuracy and 73% sensitivity for 5 epoch, when spiral and wave drawings were combined. We observed that the model was under-fitting as the train loss was much higher than the validation loss for 128*128 scale images, hence we changed the size of the images to 256*256, Figure 13 shows the train loss is lower than the validation loss and thus resolved the issue and the confusion matrix. The models accuracy is better but the sensitivity is low.

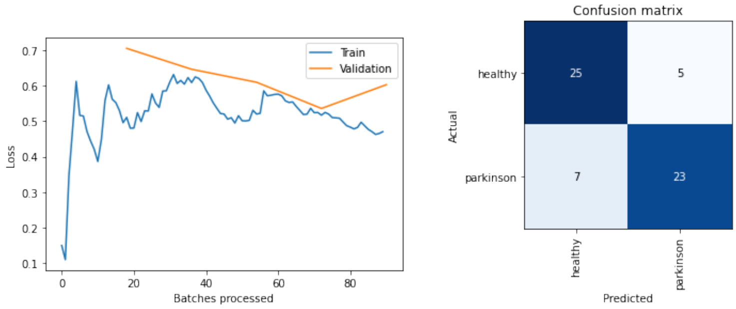

Figure 13: Resnet 34 Train Loss and Confusion Matrix

5.4.2 Resnet 50

Resnet 50 model is same as Resnet 34 but with increased number of layers. With this model we obtained the accuracy of 81.6% and 73% sensitivity which remains same as the Resnet 34 model. The specificity of the model is 90%, as shown in the figure 14 our model identify 27 correctly as healthy out of 30 samples.

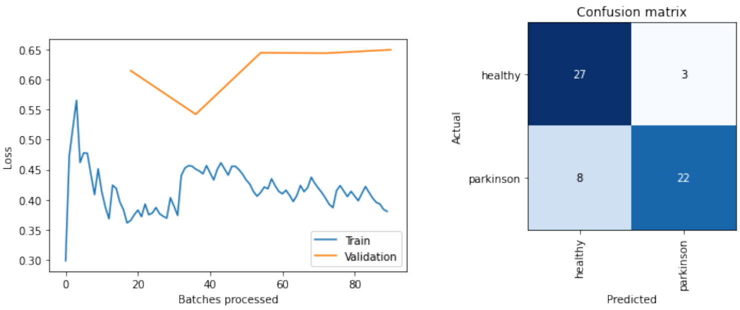

Figure 14: Resnet 50 Train Loss and Confusion Matrix

5.4.3 Vgg19

From Vgg19 a accuracy of 83% was achieved. Sensitivity in medical diagnosis is ability of the model to correctly classify the number of diseased from the healthy, Vgg19 helped in achieving 86% in sensitivity which is a vital index in medical diagnosis, albeit the specificity is lower compared to Resnet models. The confusion matrix from figure 15 it can be inferred that 24 cases are correctly identified by Vgg19 as Parkinson affected out of 30 samples.

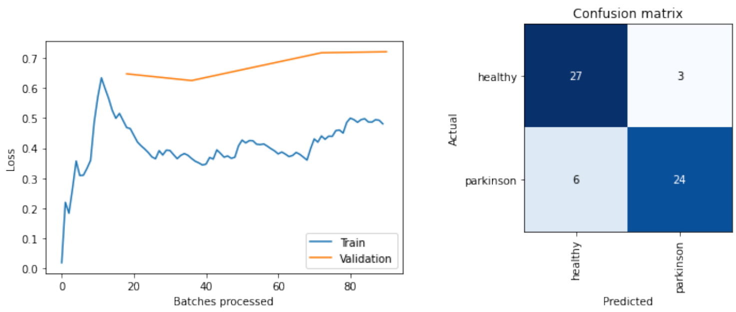

Figure 15: Vgg19 Train Loss and Confusion Matrix

Table 5: Accuracy of the models for Wave and Spiral data

Method	Accuracy(%)	Sensitivity(%)	Specificity(%)
Resnet 34	85	73	96
Resnet 50	81.6	73	90
Vgg19	83	86	80

5.5 Comparison of Developed Models

Table 6: Comparison of Developed Models for Different Case Studies

Method	Data	Accuracy(%)	Sensitivity(%)	Specificity(%)
Resnet 34	Spiral	83.33	73	93
Resnet 34	Wave	83.33	83.33	83.33
Resnet 34	Fusion	85	73	96
Resnet 50	Spiral	83	86	80
Resnet 50	Wave	73	73	73
Resnet 50	Fusion	81.6	73	90
Vgg19	spiral	80	80	80
Vgg19	Wave	90	93	80
Vgg19	Fusion	83	86	80

The table above shows the comparison of the all the models we have implemented for the analysis in this research project, from the table it can be observed that results for Resnet 34, Resnet 50 and Vgg19 are tabulated for different types of hand drawn sketches such as wave, spiral and both combined. It can be inferred from the table that the Vgg19 performs the best in this project for wave based data providing an accuracy of 90% and 93% sensitivity. In medical diagnosis sensitivity plays a vital role as the sensitivity is ability of the model to correctly classify the number of PD affected from the healthy, Vgg19 performs better for all the data as we see the model provides better sensitivity rate for spiral, wave and both combined. Hence Vgg19 is our best trained model. Resnet 34 and Resnet 50 lies in between, as Resnet 34 reduces the predicting ability of PD when both spiral and wave data combined. On the other hand when the number of layers are increased that is implementing Resnet 50 improves the rate of sensitivity for Wave based data but performs poorly on other types of data and did not give us the desired outcome. So it can inferred that the Vgg19 is the efficient model based on its performance and ability to correctly identify the PD from the healthy giving us the desired outcome. Figure 16 shows the framework for the detection of the Parkinson using the hand drawn sketches and how it would benefit the medical practitioners to treat the disease remotely with the help of an app.

5.6 Comparison of Developed Models With Existing Models

The table below shows the comparison of the previous studies with the results achieved in this project. There are very limited studies that are performed on wave based data-set. In this study Vgg19 outperformed for wave based sketches providing an accuracy of 90% and 86% for both spiral and wave combined. As we see previous researchers made use of meander and spiral to diagnose PD, from this research we observe that wave based sketches can improve the accuracy for the diagnosis of PD.

Table 7: Comparison Between Existing Models

Method	Data	Accuracy(%)	Author
Svm	67	Meander Sketches	Pereira et al. (2016)
NB 34	78.9	Meander Sketches	Pereira et al. (2016)
KNN	73.53	Spiral Skethes	Spadoto et al. (2010)
OCFA	88	Meander Skethes	Gupta et al. (2018)
ANN + MLP	67.84	Spiral Skethes	Spadoto et al. (2010)
Vgg19	86	Wave + Spiral	This study
Vgg19	90	Wave	This study

5.7 Conclusion

In this chapter the evaluation of all the Deep Neural Network and Computer Vision models provided a profound knowledge on this research project. This section also completes the objectives that is mentioned in the above research question, provided the evaluation of results and the models implemented. The results above also addresses other objectives and the sub objectives mentioned earlier. This research would contribute highly in the field of detection of Parkinson.

6 Conclusion and Future Work

6.1 Conclusion and Future Work

One of the early signs of the Parkinson disease is evidenced to be uneven hand motor functionality that is the physical functioning of the person. This impacts the ability of a person to draw, making use of this data for the evaluation can be inexpensive, easy and can be performed remotely. The main contribution of this research work is the proposal of the usage of drawing pattern that is more insightful and the evaluation of these patterns using the Deep Neural Network and Computer Vision techniques. The detection of Parkinson is evaluated using spiral and wave based data-set and also by combining both using the Residual Networks (Resnet 34 and Resnet 50) and Vgg19. The Resnet models failed to contribute the desired sensitivity to the project as the achieved sensitivity is very poor, where sensitivity is the main index in medical diagnosis. Vgg19 evidently outperformed and contributed desired results for all the patterns of data. From the results achieved we can conclude that the wave drawings are more insightful. The results from this research evidenced that combining the data would not be beneficial as the results that are captured in this research when the data was combined was relatively poor, noticed the decrease in the results when analysed the combined drawing patterns, thus all objectives and the sub-objectives are satisfied. This research work will be able to detect and treat Parkinson patients remotely and easily saving valuable resources improving the accessibility in rural and remote areas for early diagnosis.
In future we would like to increase the size of the data with more number cases which helps Deep Neural Network perform more accurately solving over-fitting issues and also include

new features such as speech and build multi-modal system for diagnosing Parkinson more accurately.

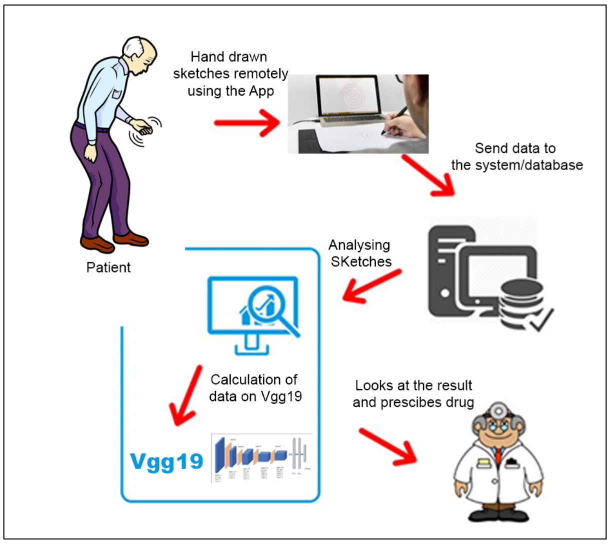

Figure 16: Future work for the detection of the Parkinson

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