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Automatic Diagnosis of Parkinson's Disease using Handwriting Patterns

Journal of Electrical Systems

Abstract: - Parkinson's Disease (PD) is a neuro-degenerative syndrome characterized by motor and non-motor signs, and early detection is crucial for effective intervention. This paper presents a novel approach for PD detection using computer vision and machine learning techniques applied to Spiral-Wave handwriting analysis. The dataset comprises frontal handwritten images obtained through the Spiral-Wave test, capturing subtle motor control differences. Our methodology involves resizing images to a standardized 200x200 pixels, converting them to grayscale, and applying thresholding for improved feature abstraction. Histogram of Oriented Gradients (HOG) is employed to capture shape and texture information. The development of a strong approach for deriving significant features from Spiral-Wave handwriting patterns and the usage of machine learning classifiers for precise PD analysis are the two main goals of this work. The emphasis is on using Random Forest and K-Nearest Neighbours (KNN) classifiers for Spiral and Wave pictures, respectively, in conjunction with the Histogram of Oriented Gradients (HOG) approach for feature extraction. For Spiral images, a Random Forest Classifier is utilized, achieving an accuracy of 86.67%. The classifier's interpretability is enhanced through an analysis of feature importance, revealing critical HOG features for distinguishing between healthy and PD-afflicted patterns. The Wave images are classified using a K-Nearest Neighbours (KNN) model, attaining an accuracy of 76.67%. Performance metrics, including precision, recall, and F1-score, offer a nuanced assessment of the KNN model's capabilities.

Keywords: Parkinson's disease, Histogram of Oriented Gradients, Random Forest and K-Nearest Neighbours (KNN)

1. INTRODUCTION:

Studies indicates that the prevalence of Parkinson's disease (PD) among individuals aged 60 and above ranges from 0 to 2 cases per 1000 people. Its prevalence rate is 1%. Next to Alzheimer's disease [l], it is the second most prevalent brain illness. Degeneration of the neurons is a result of a central nervous system condition, particularly those that affect the brain. Affected individuals may also have stiffness, sleep disorders, depression, asymmetry in posture, bradykinesia (slow movement), tremors at rest, and other symptoms. By the time the disease reaches its latter stages, individuals have coarse PD dementia and struggle to focus or sleep. Dopamine is the primary neurotransmitter that regulates the majority of the body's involuntary activities, and people with Parkinson's disease (PD) lose the nerve endings that generate it. This may provide some insight into why certain involuntary symptoms of Parkinson's disease (PD) occur, such as fatigue, irregular blood pressure, decreased peristalsis, and abrupt drops in blood pressure. As Parkinson's disease progresses, the following symptoms become worse: depression, gastrointestinal issues (such as constipation), issues urinating, difficulties with meals chewing and swallowing, loss of memory The paranormal, memory loss, loss of weight.

Discovering the difference in hand-writing and drawing abilities is one of the utmost prevalent impacts that are immediately evident between PD patients and utilized most regularly in the initial stage of analysis [2, 3]. Non-invasive techniques, including drawing spirals, waves, or other handwritten messages, allow people to be readily identified from one another as well as between those who have Parkinson's disease (PD) and those who do not [4]. Early on in the PD, handwriting and spiral sketching were discovered to be somewhat correlated by earlier researchers and doctors [5, 6]. The primary disadvantage of these diagnosis, nevertheless, is that accurate handwriting and sketch interpretation is required. Historically, the handwriting or sketching was done in the

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documents and was physically translated by interpreters who were experts in those subjects. In addition to making, it simpler to complete such duties digitally, the availability of digital devices has made machine evaluations more accurate and exact than they were in the past. These activities may be utilized to conduct reliability analysis in real-time. Some of the common elements found in the sketches may be thought of as possible markers to distinguish between various subject groups, such as healthy individuals and PD patients [7, 8].

2. CHALLENGES

There are Mainly two features they are Motor and Non-Motor. Early-stage motor characteristics regarded as the "classical or cardinal". Parkinson disease motor characteristics are Bradykinesia, stiffness, trembling, and changes in gait. Later stages having motor characteristics. These motor characteristics typically coexist with preceding ones and are not well treated by dopaminergic drugs. They are changes in posture, freezing of gait, changes in balance, dysphagia, and dysarthria.

Early on, non-motor characteristics are apparent. At the time of diagnosis, not unusual. They might occur before the advent of motor characteristics sleep problems, autonomic dysfunction, neuropsychiatric symptoms, hypomia, mild cognitive impairment, pain, and somatosensory abnormalities. Later phases having non-motor characteristics. At this point, early non-motor traits often continue and get worse are Dementia

Parkinson's Disease (PD) Detection:
- Random Forest Classifier achieved an accuracy of 86.67%.
- K-Nearest Neighbours (KNN) model attaining an accuracy of 76.67%.

3. LITERATURE SURVEY:

In-depth reviews utilizing the gathered articles categorized by brain illness are provided in this poll. Deep Siamese CNN was created by Atit Mehmood et al. [9] to forecast the phases of Alzheimer's disease categorization. Nonetheless, the approach offered a more thorough evaluation for obtaining valuable data from the MRI slices. However, it didn't look at how models were used for computer-aided diagnosis issues.

The CNN architecture for the classification challenge was provided by Dr. Rachna Jain et al. [10]. While it was able to extract useful features for the classification job, fine-tuning was unable to enhance overall performance. Residual neural networks were created by Farheen Ramzan et al. [11] to do illness categorization.

Memedi et al. [12] suggested research that would use machine learning algorithms to separate out episodes and peak dosage dyskinesia founded on spiral data gathered via telemetry touch screen devices in the household surroundings. The data was stripped of a number of characteristics, which were then fed into the machine learning classifiers. They trained the inputs for the creation of automatic systems using Support Vector Machine, Random Forest, and MultiLayer-Perceptron (MLP), and discovered that MLP outperformed all other classifiers with an accuracy of 84%.

The research by Kotsavasiloglou et al. [13] was based on how the pen point travelled over the pad while the PD and healthy patients drew straightforward horizontal lines. They used the basic drawings to extract attributes, which they then used to train machine-learning algorithms to differentiate between the PD and healthy participants. To train the inputs for creating an automatic system, they have employed a variety of classifiers, including Naïve Bayes, Logistic Regression, Support Vector Machine (SVM) and Random Forest classifiers. The study employed accuracy, Area Under the Curve, True Positives (TP), and True Negatives (TN) as performance measurements. They obtained a TN of 0.95, TP of 0.88, and accuracy of 91%.

Zham et al. [14] presented the research that employed pen pressure and speed as two criteria to identify PD participants at various phases of the disease. They have identified characteristics from the drawings and put up a plan that can found a relationship between the features and the degree of PD severity. Lastly, the Mann-Whitney trial was run to confirm the training's findings that these techniques may be used to identify various phases of Parkinson's disease. They found that the correlation factor varied significantly depending on the stage of Parkinson's disease.

In research that Aich et al. [15] suggested, PD patients were distinguished from non-patients using a speech dataset. To identify the best characteristics that may be utilized to train various classifiers, they have employed a

variety of feature selection strategies. Main component study is the feature selection approach that was applied in that investigation. Ultimately, two sets of datasets the unique feature sets and the PCA-based input sets were used in a performance of comparison research employing non-linear decision tree-based classifiers. The best classifier among them was determined to be the random forest classifier (RFC), and the performance of the PCA-based input sets outperformed the original input sets. Using PCA-based input sets and an RF classifier, the highest accuracy of 96.83% was discovered.

To categorize patients as Parkinson's disease (PD) or Healthy person, Wang et al. [16] used 401 speech biomarkers dataset and 12 machine learning models. They developed a bespoke Deep-Learning model that had a 96.45% classification accuracy, but because of its high memory needs, the model was costly.

A linear classification model having 95% accuracy was used by Alkhatib et al. [17] to describe the shuffling gait of Parkinson's disease patients. Their study concentrated on the patient's gait, and subsequent research promoted the inclusion of audial and sleep data to improve the outcomes. Brain MRI data were exposed to spatial-temporal study by Ricciardi et al. [18]. They used KNN, random forests, and decision trees to identify Mild-Cognitive Impairment (MCI) in PWP.

The dataset was tiny, though, therefore artificial data augmentation was required et al. [19]. For patients with neurological disorders, A. U. Haq and colleagues et al. [20] used L1 support SVM without input identification on vowel vocalization datasets. Their study did not take into account healthy people in a lower age range; instead, it concentrated on patients between the ages of 46 and 85. As minor non-motor symptoms may go unnoticed during a subjective examination by a physician, Mei et al. [21] highlight the significance of machine learning in the detection of Parkinson's disease. They evaluate 209 papers according to datasets, machine learning techniques, and results attained.

Prior investigate on gait, MRI scans and genetic data has been used to forecast Parkinson's disease; however, little study has been done on aural impairment for initial identification. For example, using an SVM model, Bilal et al. [22] looked at genetic data to forecast when Parkinson's disease (PD) will manifest in elderly people. While in this survey report provides an enhanced SVM model with an accuracy of 0.9183, they trained an SVM model to obtain an accuracy of 0.889.

These findings support the advantages of using auditory data rather than genetic data for the categorization of Parkinson's disease. Using keystroke data from the UCI telemonitoring dataset, Raundale, Thosar, and Rane et al. [23] trained a Random Forest classifier to forecast the severity of Parkinson's disease (PD) in elderly people. Audio data is used by Cordella et al. [24] to categorize PWP, However, MATLAB is a major component of their models. Our study makes use of open-source, quicker, and more memory-efficient Python models.

A unique technique for identifying Parkinson's disease patients using kinematic data taken from handwritten drawings was presented by Rohit Lamba et al. in [25]. The high imbalance in the data necessitates the application of the SMOTE technique, information gain approach for feature selection, and ensemble technique Adaboost for training, which yielded a 96% accuracy rate. But this study simply predicts the PD; it makes no predictions about the severity of the illness.

Two distinct CNNs were trained by the authors of the study et al. [26] to analyze the spiral and wave drawings' drawing patterns. In et al. [27], Catherine Taleb et al. produced accuracies of 94%, 92%, and 88%, respectively, using a Multi Class support vector machine to predict H&Y stage, UPDRS and total UPDRS scores in order to detect Parkinson's disease. Principal component analysis is employed in this study et al. [28] to decrease the dimensionality of sensor data. Six random forest models with an accuracy of 89.4% are trained using k-fold cross validation.

A strategy for categorizing the severity of Parkinson disease is developed in the study et al. [29]. In order to predict UPDRS scores, they constructed a deep neural network employing 50 neurons and three hidden layers, utilizing Parkinson's Telemonitoring Voice Data from the UCI Machine Learning Center. The accuracy attained in the article for motor UPDRS is 82%, but the accuracy for total UPDRS is 62%. If more examples with more attributes were utilized for training, the accuracy may have been higher.

MRI PPMI Image data is the basis for the model employed in this article et al. [30] to categorize people as either healthy or having Parkinson's disease. They trained utilizing CNN with 35 layers, using a specific sort of pictures (3T T1). SMBO for choosing the hyperparameters. The model's accuracy was 95%, and its AUC curve was 0.98.

The model employed in the paper et al. [31] classified the images as HC and PD based on PPMI, ADNI, and HCP data.

The accuracy of the UNET model was 84.7%, whereas the VGGNet model yielded 76% accuracy. Using data from the PPMI survey, the model employed in the paper et al. [32] classified as HC and PD. Numerous motor and non-motor assessments were employed in the construction model. The upgraded probabilistic neural networks used in the article yielded an accuracy of 98.6%.

4. DATASET DESCRIPTION:

We acquired the data Parkinson's disease hand-writing patterns dataset sourced from Kaggle.

The dataset consists of 102 spiral and 102 wave hand-writing patterns. The several data augmentation techniques is are applied on the dataset to detect Parkinson's disease in patients. The dataset mainly divided in two sub folders: they are spiral and wave which is further divided into two sub folders test and trained foreach folder. We took 80% of data for training and 20% of data for testing in both spiral and wave folders.
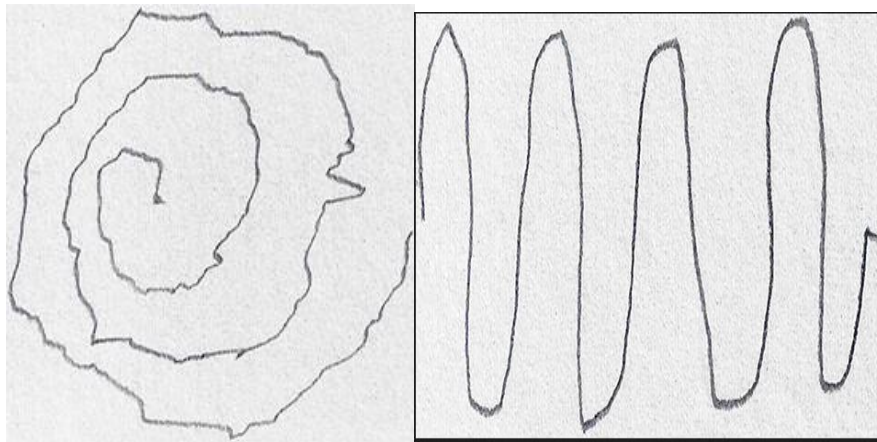

Fig-1: Input Images of Spiral and Wave Patterns

These are the handwriting patterns in the form of spiral and wave. They are taken as feature to identify the Parkinson's positive in the patients which will help in quick time of detecting the Parkinson's positive in huge amount of patient data.

In this dataset, the spiral-wave patterns which are handwriting patterns of patient have a variation from the healthy person where there will be a little zig-zag form and a little deviation in patterns when compared to healthy person have smooth curves and lines. By this our method will detect whether the person is Parkinson's patient or healthy.

5 METHODOLOGY:

In the study, this paper is used to detect whether Parkinson's disease is present in the patient or not by handwriting patterns. For the detection we used the Random Forest classifier algorithm for spiral patterns and KNN algorithm for the wave patterns.

5.1 Data Augmentation:

"Data augmentation" is a machine learning approach that is commonly used to improve the variety of the training dataset by performing various modifications to the current data, especially in computer vision problems. Data augmentation is the process of making little changes to handwriting patterns while preserving the most crucial features and introducing unpredictability to the data. The model's performance and generalization may be improved by exposing it to a wider range of picture variants.

Rotation: To replicate several points of view, rotate the image by a specific angle (such as 90° or 180°).

Brightness Adjustment: It is a data augmentation technique that involves changing the intensity of pixel values in an image, making it either brighter or darker.

Channel Shift Range: Channel shift range is a data augmentation technique that involves shifting the values of colour channels within a certain range, introducing variations in colour tones.
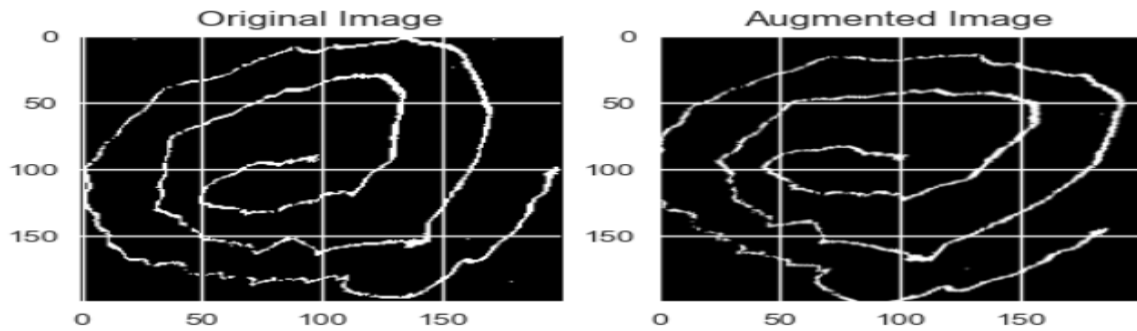

Fig-2: Original Image vs Augmented Image

5.1.1 Feature Abstraction using Histogram of Oriented Gradients (HOG):

Histogram of Oriented Gradients was employed to capture the local intensity gradients and edge directions in pre-processed image. The HOG descriptor for a given image region is computed by dividing the region into cells and calculating the histograms of gradient orientations within each cell. The final descriptor is formed by concatenating these histograms.

Cell Division and Gradient Calculation: An essential first step in the HOG process is to divide the image into cells. The histograms are produced within each cell, which functions as a localised zone, in order to capture the variations in gradient orientations. Depending on the required level of granularity and the properties of the pictures, selecting the appropriate cell size is crucial.

Usually, methods like the Sobel operator, which determines the image's first derivatives in both the horizontal and vertical dimensions, are used to compute the gradients. The gradient orientation and magnitude in each pixel are then ascertained using these gradient values.

Significance in Object Detection: HOG has been a popular choice for problems involving object detection, particularly in computer vision applications. Its efficacy stems from its capacity to extract an object's structural information from the gradient orientation distribution. Because of this, HOG is very useful for identifying objects with distinct textures and edges.

$$HOG(x,y)=[hist_1, hist_2, ..., hist_n] \qquad ----->eq(1)$$

where $hist_i$ represents the histogram of gradient orientations for the ith cell

5.1.2 Machine Learning Methods:

A data analytics technology called machine learning trains computers to learn from experience, much as humans and animals do naturally. Instead of using a preset equation as a model, machine learning algorithms 'learn' from data directly using computational techniques. supervised and unsupervised machine learning methods are subdivided. Support vector machines, k-nearest neighbours, Naive Bayes, and neural networks are popular techniques for classification. Neural networks, regularization, stepwise regression, linear and nonlinear models, and regularization are examples of common regression techniques. Fuzzy C-means clustering, hierarchical clustering, and k-means and k-medoids clustering are common clustering techniques.

Random Forest Classifier (Spiral Images):

The Random Forest approach is applied to both classification and regression problems. We are utilizing it for categorization in this instance. The random forest, as its name implies, is made up of a large number of decision trees. By using the votes of decision trees that have been trained on subsets of the training data, the random forest classifiers make their determination. Next, the final projection is made based on the popular vote. These data subsets are created using an ensemble approach known as bagging, which is frequently applied to high variance models since it lowers variance and lessens the possibility of overfitting.

The core of Random Forest is ensemble learning, a method that integrates several models' predictions to improve performance as a whole. This ensemble is created in the Random Forest setting using a technique known as bagging, which is short for bootstrap aggregating. To promote diversity in the models, bagging entails training each decision tree on a random subset of the training set. Random Forest combines these several trees predictions to attain robustness and generalizability.

When high-variance models overfit, they perform remarkably well on training data but poorly on fresh, untested data. By averaging the forecasts of several trees and lowering the model's overall variance, Random Forest's ensemble approach lessens this danger.

The HOG characteristics that were taken out of Spiral pictures were used to train the Random Forest Classifier. The sum of the individual decision trees is known as the random forest's decision function F(x):

$$F(x) = \frac{1}{N}\sum_{i=1}^{N} f_i(x) \qquad \text{-----}>eq(2)$$

where $f_i(x)$ is the result of the ith decision tree and N is the total number of trees in the forest.
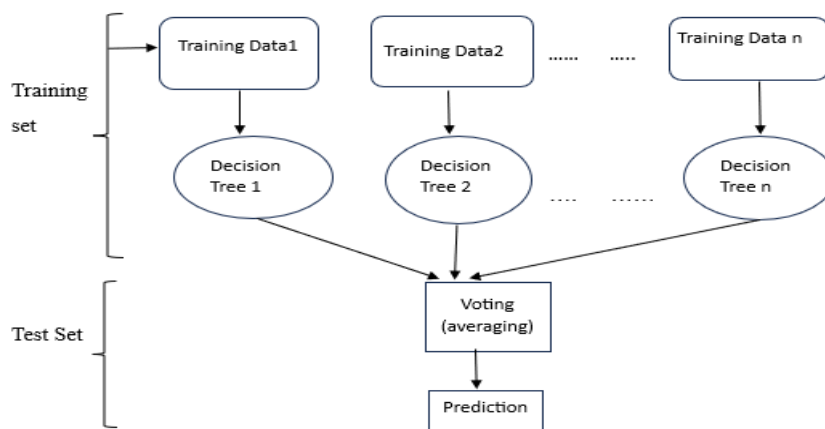

Fig-3: Architecture of Random Forest Algorithm

K-Nearest Neighbours (Wave Images):

The most basic machine learning algorithms, K-Nearest Neighbour, is grounded on the supervised learning approach. The K-NN method classifies a new data point based on similarity after storing all the relevant data. This indicates that the KNN technique may be used to quickly classify newly discovered data into a well-suited category. Although the KNN technique is mostly utilized for classification issues, it may also be used for regression. Because it saves the dataset and acts on it while classifying, it is also known as a lazy learner algorithm. This is because it does not learn from the training set right away.

KNN's Distance Metrics: The idea of similarity, which is frequently assessed using distance metrics, is the basis of KNN. Minkowski, Manhattan, and Euclidean distances are examples of common distance measures. The distance measure should be chosen depending on the properties of the data because it might have a big impact on the algorithm's performance.

Selecting a hyperparameter, 'k'

The KNN parameter 'k' denotes the quantity of closest neighbours taken into account during the classification process. Choosing 'k' is an important part of fine-tuning the algorithm. A large 'k' can cause over smoothing and loss of detail, while a little 'k' could provide a noisy model. The best value for 'k' may be found for a grid search using cross-validation and

Test samples are categorised using KNN according to their k nearest neighbours in the feature space. A voting mechanism determines the class label of a test sample by assigning the class with the highest number of votes among its k neighbours. The mathematical expression for this decision rule is:

$$\hat{y} = \arg\max_{j} \sum I(y_{i=j}) \qquad\qquad \text{------>eq(3)}$$

where I is the indicator function and y_i is the class label of the ith neighbour.
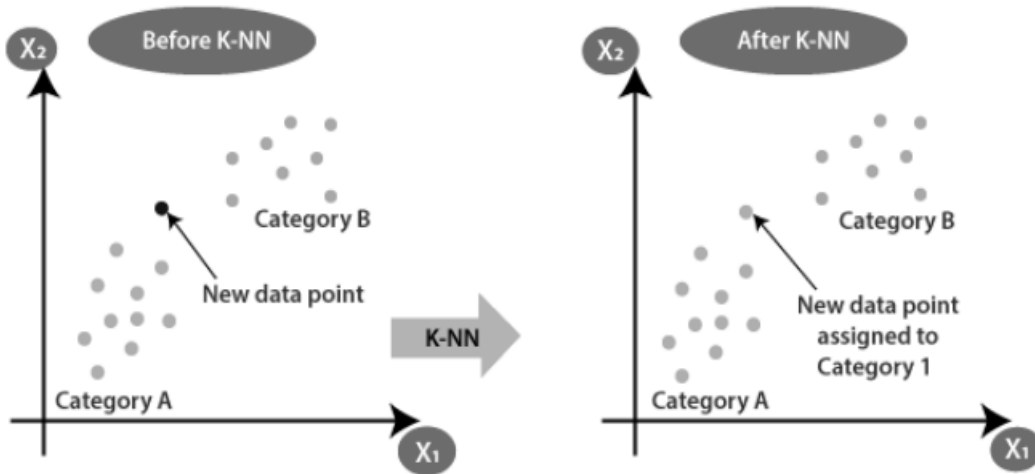

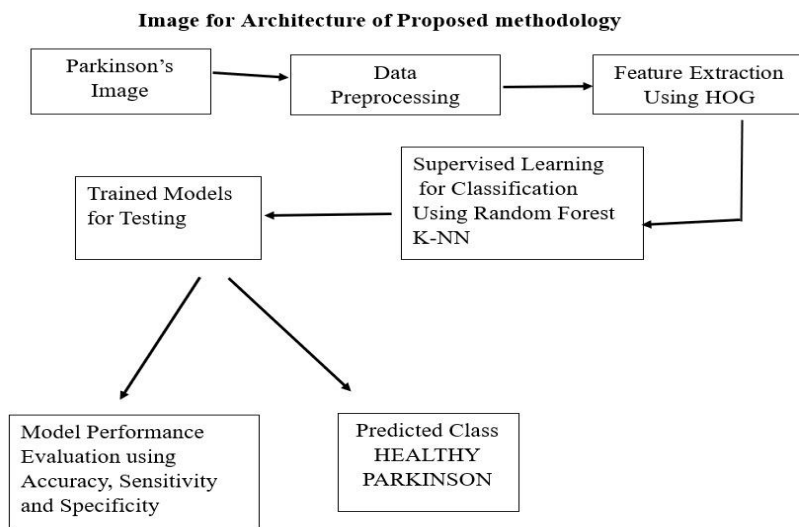Fig-4: Architecture of K-NN Algorithm

Fig-4: Architecture of Proposed Methodology

5. RESULTS AND DISCUSSIONS:

This study describes a method for detecting Parkinson's illness using spiral and wave sketching using Random Forest and k-Nearest Neighbour. For categorization purposes, the studies mostly used spiral and wave sketch data from both healthy participants and Parkinson's sufferers. The study appears to be rather good at distinguishing between the sketches created by participants in good health and those done by Parkinson's sufferers. We took the spiral and wave handwriting pattern dataset by applying the Histogram of Gradient Function (HOG) the input features are extracted and forward to our methodology. The spiral images are forwarded to Random Forest classifier which will classify the spiral patterns in to Parkinson's patients and Healthy person. The wave images are given to k-Nearest Neighbour Algorithm (k-NN) which classifies as respectively.

The model displayed the following data: for spiral images: average f1 score of 87.5%, average recall of 82.35%, average precision of 93.34%, and accuracy of 86.67% and for wave images: average f1 score of 72%, average recall of 90%, average precision of 60%, and accuracy of 76.67%

Assessment is a crucial step in the machine learning process because it lets us assess how successfully a model that has been trained can complete a task. Conclusions of the study According to Parkinson's Disease using handwriting patterns, it was possible to create an accurate model to identify the detection of the patients. Typical evaluation metrics, such as F1-Score, Specificity, Sensitivity, Testing and Training Accuracy, and Accuracy, were incorporated into this study to measure the prediction performance.

- *Training and validation accuracy*: On a validation dataset, the performance of the model is assessed during the training process that is separate from the training data. Usually, the training and validation accuracy are displayed against time to monitor the model's performance and detect overfitting.
- *Test accuracy:* After the model has been trained, a separate test is used to gauge its performance. This provides us with a rough idea of how efficiently the model will extrapolate to brand-new, untested data.
- *Confusion matrix:* In a classification problem, a table called a confusion matrix. A confusion matrix lists all of true positives, true negatives, false positives, and false negatives to each class. It is capable of calculating a number of measures, including F1 score, recall, and precision.
- *Precision, recall, and F1 score:* These measures are employed to assess a model's effectiveness in a classification task, particularly when the dataset is imbalanced. Precision measures the percentage of true positive estimates produced out of all positive forecasts, but recall assesses the percentage of true positive predictions ended out of all authentic positive forecasts. The harmonic average of memory and precision is the F1 score.

$$Accuracy = \frac{tp + tn}{tp + fp + fn + tn}$$

$$Precision = \frac{tp}{tp + fp}$$

$$Recall = \frac{tp}{tp + fn}$$

$$F - measure = \frac{2 \times (recall \times precision)}{recall + precision}$$

6. CONCLUSION AND FUTURE SCOPE:

Since no one test can definitively determine the presence of Parkinson's disease, this research attempts to identify the condition based on an individual's handwriting. Although the classifier's performance and the technique covered in the paper seem to be rather good right now, there is still room for improvement. The number of data samples could be greatly increased, different drawing styles other than spiral and wave must be used, and selecting some cutting-edge architecture for the second section could be done several times over. These are the improvements that could be made to the current methodology. However, the current system gave us great confidence that this sort of technology could be used in robust production environments and real-life situations.

Subsequent research endeavors may investigate the application of sample methodologies, such as over-sampling or under-sampling, to achieve dataset balance. Improving performance and eliminating the bias against the majority class would both benefit from this. Particular datasets were used in the current study's model building and assessment. In order to evaluate the produced models' robustness and generalizability, future research may test them on external datasets or actual data. This would offer light on how well the suggested techniques work with various demographics and how applicable they are in real-world scenarios. We can improve the field of PD
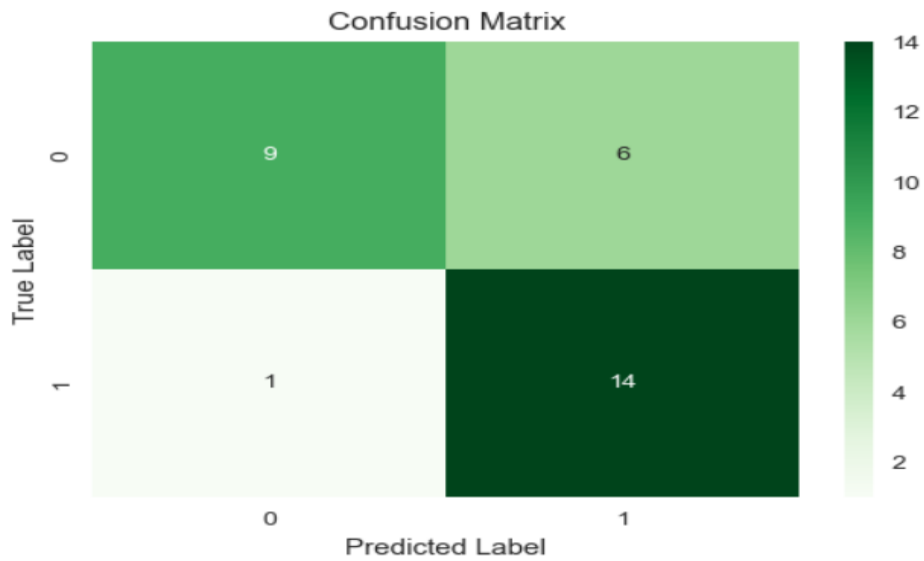
identification using handwriting pattern data and aid in the creation of precise, dependable, and clinically useful diagnostic tools by tackling these future research topics.

Confusion matrix:

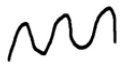**For spiral drawings:**
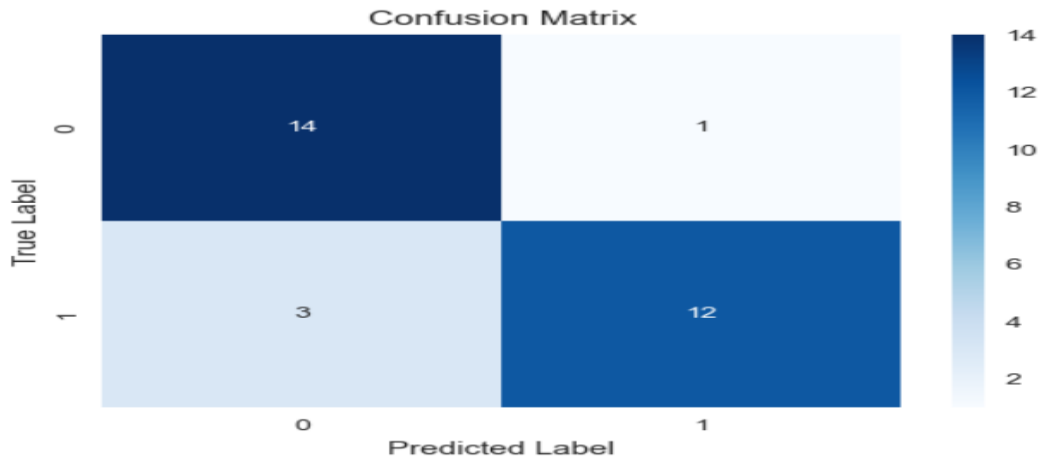
For wave drawings:

Model	Training Accuracy	Sensitivity	Specificity	Validation Accuracy	Testing Accuracy
Random Forest	100%	0.8	0.93	100%	86.67%
KNN	100%	0.73	0.8	100%	76.67%

Spiral Parkinson's	Spiral healthy	Wave Parkinson's	Wave Healthy

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