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Early Detection of Parkinson's Disease Using Machine Learning

Abstract: - A hallmark of Parkinson's disease is the degeneration of dopaminergic neurons in the midbrain's substantia nigra pars compacta. However, machine learning is needed to design and implement early Parkinson's disease detection. by using machine learning methods such as CNN and SVM, which can reliably identify voice signals and spiral images to identify early indications of Parkinson's disease. Using machine learning on handwriting, tremor, and gait datasets, the method addresses the shortcomings of individual analyses for a more complete diagnosis solution by investigating relationships between symptoms. This increases accuracy. When voice and spiral drawing data were combined, Parkinson's disease diagnosis accuracy showed promise, with the machine learning model successfully differentiating between unaffected patients and those who were affected. This observation suggests a viable path for precise Parkinson's disease diagnosis: an integrated method that combines machine learning techniques with data from spiral drawings and voice.

Keywords: Machine learning, Python, voice dataset, spiral dataset, Support Vector Machine (SVM), Convolutional Neural Network (CNN).

I. INTRODUCTION

Diseases affecting the nervous system are a major health concern due to their high mortality rates. Nervous system diseases are projected to cause more deaths than cancer soon [2]. Parkinson's disease is one such illness that causes specific motor symptoms due to the loss of dopaminergic neurons in the midbrain's substantia nigra pars compacta.

Early detection is crucial for timely intervention and improved patient outcomes, but current diagnostic methods often lack the necessary sensitivity to identify the disease in its early stages.

While machine learning techniques such as support vector machines (SVM) and convolutional neural networks (CNN) have shown promise in various medical applications, their specific application to voice datasets and spiral images for early detection of Parkinson's disease remains an underexplored area. It is known that dopamine deficiency in the striatum is responsible for motor skills in Parkinson's disease [1]. While clinical evaluations are currently the primary method for diagnosing the disease, they may not be able to identify subtle early indicators. By utilizing cutting-edge machine learning algorithms like SVMs and CNNs to analyze voice sounds and spiral drawings, a more comprehensive diagnostic strategy can be developed, overcoming the limitations of current approaches and improving sensitivity and specificity. This work aims to bridge the gap in the early diagnosis of Parkinson's disease by evaluating voice samples and spiral imagery using SVM and CNN algorithms. It is anticipated that this approach will significantly improve the effectiveness and accuracy of early-stage Parkinson's disease identification.

By examining the connections between speech signals and motor function as represented in spiral drawings, this research seeks to develop a distinct and reliable diagnostic paradigm. The creation of a trustworthy and accessible early detection tool could potentially lead to better patient outcomes in the treatment of Parkinson's disease. The ultimate goal of this work is to improve the early diagnosis of Parkinson's disease by utilizing CNN and SVM

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algorithms with spiral and audio datasets. By correlating speech signals and motor function in spiral images, it is expected that the accuracy of the diagnosis will increase. Successful validation of this approach could lead to the development of a reliable machine-learning-based diagnostic tool for improved treatment of Parkinson's disease.

II. LITERATURE REVIEW

The neurodegenerative condition known as Parkinson's disease (PD) is characterized by both motor and non-motor symptoms.

Early detection is crucial for effective disease management, leading researchers to explore the use of machine learning (ML) techniques for timely diagnosis. Studies have shown that ML systems utilizing speech signals have the potential for non-invasive and early detection methods [3].

By analyzing multiple types of speech signals, these systems can contribute to a more accurate and timely diagnosis. The understanding of Parkinson's genetics has undergone significant changes, as highlighted by M.J. Farrer in a comprehensive review [1]. Identifying genetic factors is essential for a nuanced understanding of the disease. Deep learning techniques, specifically convolutional neural networks (CNNs), have been applied to both voice and spiral datasets, demonstrating their potential for early PD diagnosis [10] and [12]. The intricate patterns detected by CNNs showcase their ability to identify subtle signs of the disease. Datasets such as Hand PD [4] and Parkinson's Drawings [5] provide a visual dimension for ML applications, opening up new possibilities for image-based diagnostic tools. While traditional methods for Parkinson's diagnosis have relied on clinical assessments, they have limitations in accuracy and early detection [2]. Therefore, it is essential to augment these methods with advanced technologies like ML. While SVMs have been used for PD diagnosis [6], a comparative analysis with CNN models reveals the strengths and weaknesses of each approach. SVMs, with their interpretability, contrast with the intricate pattern recognition capabilities of CNNs. Emerging trends, such as the integration of diverse datasets [13], hold promise for refining diagnostic models. However, challenges still exist, and continuous interdisciplinary collaboration is necessary to address ethical concerns.

In conclusion, the integration of ML, particularly deep learning techniques, into Parkinson's disease diagnosis presents a transformative approach. As technology advances and datasets expand, the potential for early detection and effective management becomes increasingly viable.

III. METHODOLOGY

"Machine learning techniques can be effectively utilized to solve problems with the lowest possible error rate. In this study, we use a speech dataset related to Parkinson's disease, obtained from the UCI Machine Learning library. By combining spiral drawing inputs from both normal individuals and those with Parkinson's disease, our system can produce accurate results. Our proposed hybrid approach incorporates both spiral drawing and speech data from patients, resulting in reliable findings. This integrated approach allows physicians to determine the presence and severity of the illness and provide appropriate treatment. Additionally, we suggest including handwriting samples, tremors, and gait as part of the dataset for Parkinson's disease diagnosis. By identifying correlations between these symptoms, we can improve the accuracy of our diagnosis. While analyzing each symptom separately may have limitations, such as the complexity of handwriting and the potential influence of other factors on motor movement, incorporating multiple symptoms can help mitigate these issues. Furthermore, previous studies have shown that using breath samples alone may not yield clinically meaningful results for speech recognition.

Therefore, we have also included additional steps, such as noise removal and speech segmentation, to improve the accuracy of our approach. By incorporating multiple symptoms, we aim to address the limitations of relying on a single symptom for diagnosis.

A. Proposed System

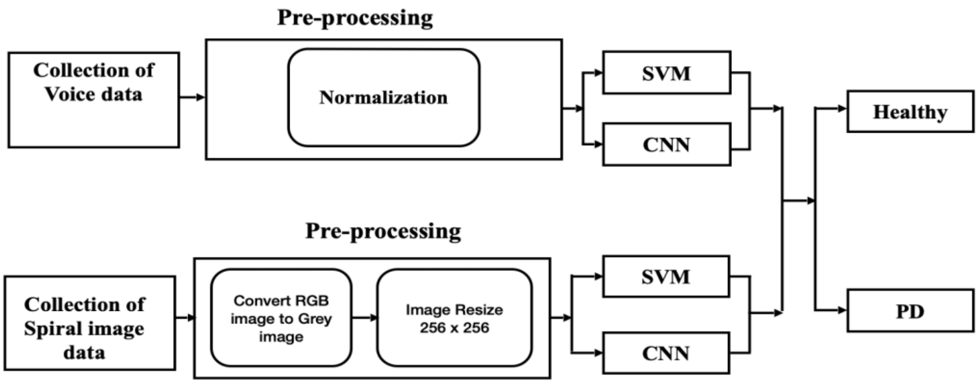


Figure 1 Proposed system

B. Data sets

a. Voice

To diagnose diseases, data is collected from Kaggle and then processed.

- The dataset consists of measurements from 31 individuals' biological voices, 23 of whom have been diagnosed with Parkinson's disease (PD).

- Each row in the table represents one of the 181 voice recordings from these individuals, with each column representing a specific voice measure (referred to as the "name" column).

- The main purpose of this data is to distinguish between individuals with PD and those who are healthy, as indicated by the "status" column, where a value of 0 represents a healthy individual and a value of 1 represents someone with PD.

- The data is stored in CSV ASCII format, with each row in the CSV file containing one instance of a voice recording. Each patient has about six recordings available, with the patient's name listed in the first column.

b. Spiral

The second data set was retrieved from Kaggle and then processed.

- There is a spiral pattern in the data set.

- The format of each one is PNG. There are training and testing data sets inside the data set.

- Personal details like age and gender are not disclosed. The training data includes 72 spiral drawings, with 36 created by Parkinson's sufferers and 36 by healthy individuals.

- The testing data include thirty spiral drawings in total, fifteen of which were created by patients with Parkinson's disease and fifteen by Healthy individuals.

C. Data-Pre-Processing

A. Voice data

Clean and preprocess the data, normalize the features, and handle missing values if necessary. This step is crucial to ensure the quality of the dataset.

a. Normalization

- Min-max scaling, often referred to as normalizing, is a preprocessing method for data that is used to convert numerical variables or characteristics to a range, usually between 0 and 1.

- ensuring all the variables are on the same scale without misrepresenting their relative differences is the aim of min-max scaling.

- The following formula may be used to apply min-max scaling to a feature:

(X – X_min) / (X_max - X_min) equals X_scaled.

B. Spiral Image

- Data augmentation: This involves making various adjustments to the training image to increase the diversity of the training process; This will help increase the generality and robustness of the model.

- Rescale: This parameter scales the pixel values of the image. In the case, it rescales the pixel values to [0,1] by dividing each pixel's value by 255. This is a first step to enable equipment to emulate a neural network, which can help improve convergence during education.

- Rotation_range: This parameter specifies the range of the image that can be rotated. In this case, the image can be rotated at any angle within the range of [-40,40] degrees. Width_shift_ range and height_shift_range. Parameters control the horizontal and vertical range of the image respectively. In the case, the image can be moved horizontally up to 20% of the total width and vertically up to 20% of the total height.

- Shear_range: shear moves part of the image in a fixed direction while preserving other parts. This parameter controls where the crop is applied to the image.

- Zoom_range: This parameter specifies the range of images to be randomly zooed. In this case, the image can be expanded up to 20%.

- Horizontal_flip: This parameter specifies whether the image will be allowed to flip horizontally. Randomly flipping horizontally will mirror the images horizontally, which will help make a difference in the study material.

- Fill_mode: This parameter specifies the strategy for filling new pixels that will appear after various changes such as rotation or replacement. In this case "nearest" is used; This means that the closest available pixel value will be used to write the new pixel.

a. Instruction of Models

Data splitting is a term used to describe the process of training, validating, and testing models.

i. Training Set: A machine learning model is trained using the training set, which is a subset of the dataset. It is used to train the model to identify patterns and correlations within the data and comprises most of the data.

ii. Test Set: This entirely separate subset is used to assess how well the trained model performs in the end. The test set acts as a stand-in for hidden, real-world data. It offers an assessment of the model's generalization performance and aids in evaluating how effectively the model functions in real-world situations

IV. FEATURE DESCRIPTION

A. Voice dataset

Table 1 Voice Attributes

Attributes	Description
Name	ASCII subject name and recording number

Table 1 Voice Attributes

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	Several measures of variation in fundamental frequency
MDVP: Shimmer, MDVP: Shimmer(dB),Shimmer:APQ3,Shimmer:APQ5,MDVP:APQ,Shimmer:DDA	Several measures of variation in amplitude
NHR,HNR	Two measures of ratio of noise to tonal components in the voice
status	Health status of the subject (one) - Parkinson's, (zero) – healthy
RPDE,D2	Two nonlinear dynamical complexity measures
DFA	Signal fractal scaling exponent
spread1,spread2,PPE	Three nonlinear measures of fundamental frequency variation

B. Spiral dataset

Extracting statistical features from an image using the Gray Level Co-occurrence Matrix (GLCM) technique.

GLCM is a technique used to describe the spatial relationship between pixels in an image. It quantifies how often pairs of pixel intensities with specific values occur about each other at a specified distance and direction within an image. After computing the GLCM, it extracts four statistical features: Contrast, Energy, Correlation, and Homogeneity.

i.Contrast:
Contrast is the measure of the contrast between a pixel and its neighbouring pixels throughout an image. Calculates local changes in the grey level correlation matrix(GLCM). More contrast compared to the difference between adjacent pixels makes the image more beautiful.

Calculated as the sum of the squares of the differences between the pixel values of all possible pixel pairs in the GLCM and their averages. Similar results indicate more texture or roughness in the image.

ii.Energy:
Energy, also known as angular second time, represents the uniformity or smoothness of the beautiful image. Indicates the distribution decision of pixel pairs by evaluating the sum of squares of the point in GLCM. Higher

energy values indicate a smoother texture where pixel values are similar across the images. For example, lower energy values indicate more tissue. The results show that there is a lot of complexity and a large number of textures with different patterns.

iii. Correlation:

Correlation measures the line between the grey levels of adjacent pixels in an image.

Shows the correlation or relationship between pixel values in GLCM. Values close to 1 indicate good correlation, meaning adjacent pixels will have similar values. A value close to -1 indicates a negative correlation; This means that neighbouring pixels will have similar values. Pixels have different values. Correlation values around 0 indicate poor or no correlation between pixel intensities.

iv. Homogeneity:

Homogeneity, also known as contrast moment, measures the closeness of pixel intensities and distribution of elements in a GLCM along the GLCM diagonal. Measures the local uniformity of the beautiful images. The higher the consistency value, the closer the GLCM points are to the diagonals, which means the texture becomes more and more regular. Lower homogeneity values indicate disorganization of GLCM elements, indicating diversity and heterogeneity.

v. Stroke thickness:

This function calculates the stroke thickness of object in the binary image: Multiplies the distance between the skeleton to get the contour images; where each pixel value represents the distance from the pixel to the stroke weight, according to the skeleton.

V. MODELS

A. Support Vector Machine

A popular supervised learning technique for classification and regression problems is support vector machines (SVMs). An algorithm for supervised learning is a support vector machine. An N-dimensional hyperplane is formed and classification is performed using an SVM, which models the data into k categories. Train the SVM model using the training data. The SVM algorithm aims to find the optimal hyperplane (or decision boundary) that maximizes the margin between different classes in the feature space.

Mathematically, the linear kernel between two feature vectors x and y is given by:

K (x, y) = x ^T. y

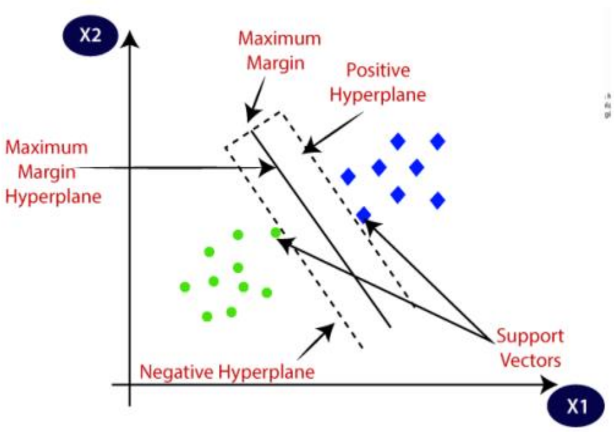


Figure 2 SVM Model

B. Convolutional Neural Network

One kind of deep neural network that is specially made for tasks requiring visual input, such as image and video recognition, is the convolutional neural network (CNN). CNNs have proven to be highly effective in a wide range of computer vision applications, including image classification, object detection, facial recognition, and more. They are inspired by the visual processing that occurs in the human brain and are particularly well-suited for handling grid-like data, such as pixels in an image.

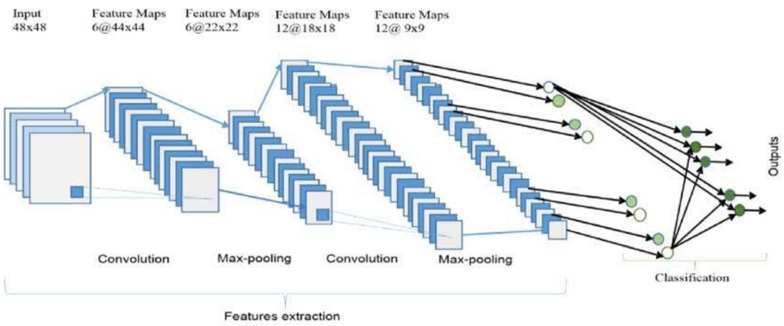


Figure 3 CNN Model

VI. RESULT

The proposed work has considered a limited data set for both. The existing work has expressed the probability of using the voice dataset of humans as an effective tool for PD diagnosis when we use the SVM model as it gives an accuracy of 87% and the CNN model gives an accuracy of 82.05%. It also expressed the probability of using the spiral dataset as an effective tool for PD diagnosis when we use the CNN model as it gives an accuracy of 93% and the SVM model it gives an accuracy of 60% However when machine learning and deep learning are the emerging techniques to be applied for healthcare sector, it requires significant execution and accurate results to demonstrate the technique. This work has suggested machine learning methods for the classification of spiral drawing images of healthy control and PD patients to aid the medical practitioner in diagnosing the diseases at an early stage.

Table 2 Result Evaluation table

Dataset	Classification model	Accuracy
Voice dataset	SVM	87%
	CNN	82.05%
Spiral dataset	CNN	93%
	SVM	60%

A.Metrics

tp:true positive, tn: true negative
fp: false positive, fn: false negative.
Accuracy: Classification accuracy is what we usually mean when we use the word accuracy. It is the ratio of the number of correct predictions to the total number of input samples.
Accuracy= correctly classified sequence/ all samples

Accuracy: Also called positive predictive value, is the proportion of relevant events in the sample. The sample was returned. Intuitively, precision is the classifier's ability to not write good example when it is not good. The higher the value, the better the classifier.

Return= tp/(tp+tn+fp+fn)

Reflection(return) is the fraction of all relevant events returned.

Recall is the ability of a classifier to intuitively find all good patterns. The higher the number, the more accurate it is.

Recall= tp/(tp+fn)

Specificity (also called negative value): Specificity related to the ability of the class to detect negative consequences.

F1 score: F1 score*((sensitivity*return) / (sensitivity + return)). Also called F score or F-measure.

When F1, it shows the balance between accuracy and return.

F1= (2*(tp/(tp+fp+tn+fn))*(tp/(tp+fn)))/((tp/tp+fp+tn+fn))+(tp/(tp+fn))

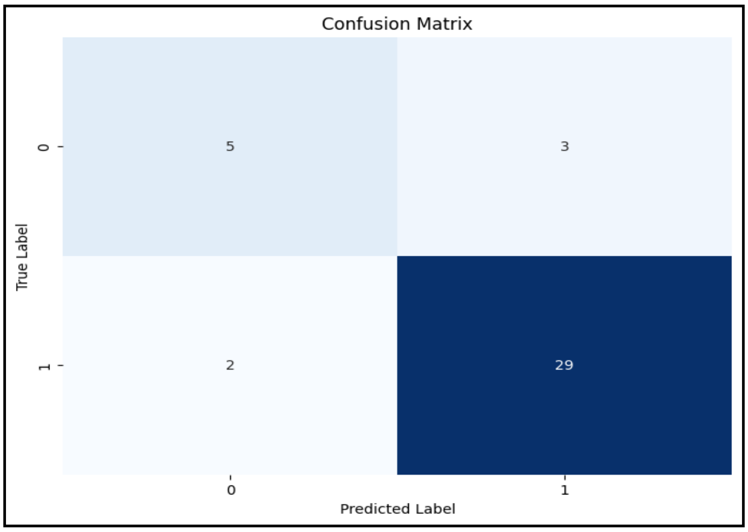


Figure 4 Confusion matrix of voice data using SVM

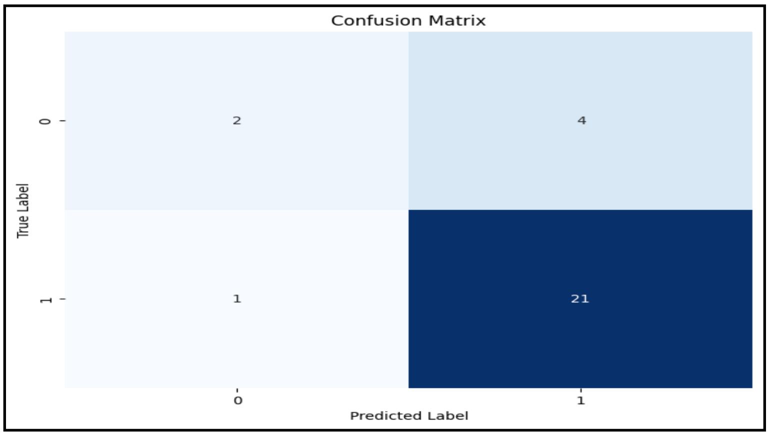


Figure 5 Confusion matrix of voice data using CNN

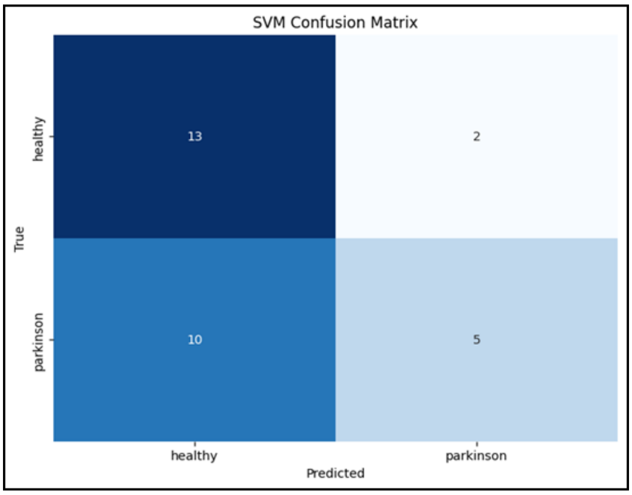


Figure 6 Confusion matrix of spiral image using SVM

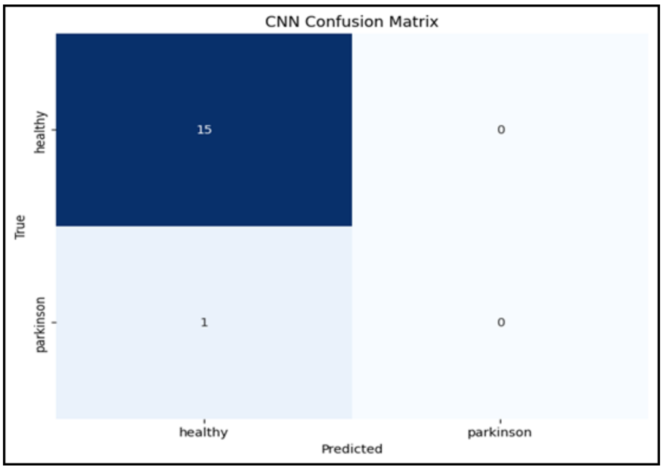


Figure 7 Confusion matrix of spiral image using CNN

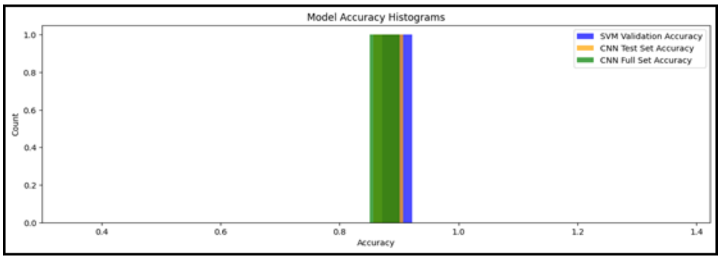


Figure 8 Model accuracy histogram for voice data set

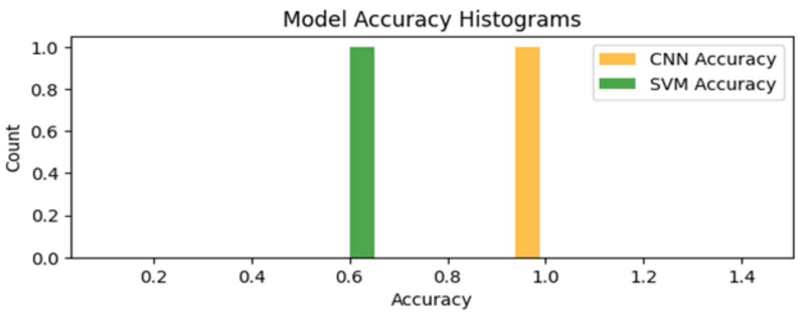


Figure 9 Model accuracy histogram for spiral data set

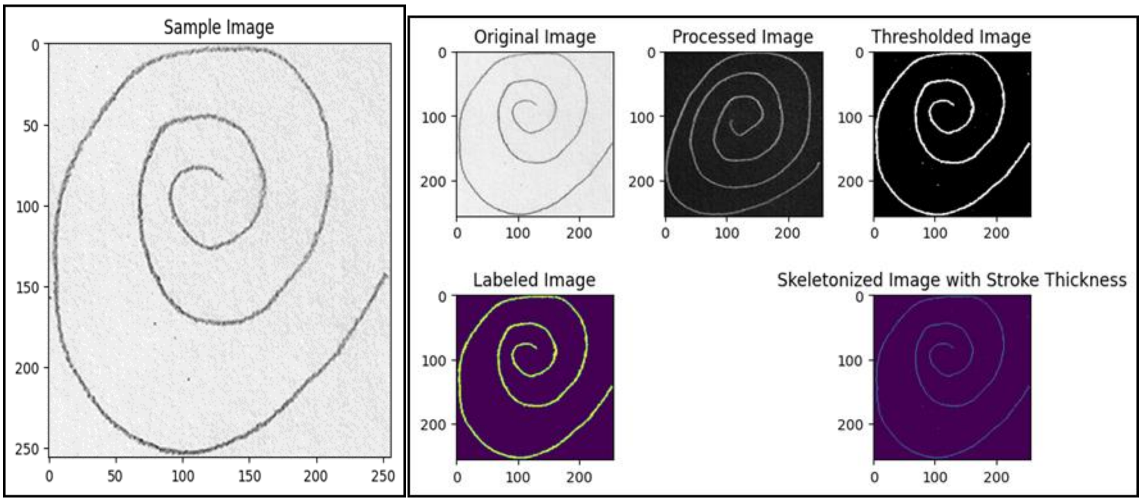
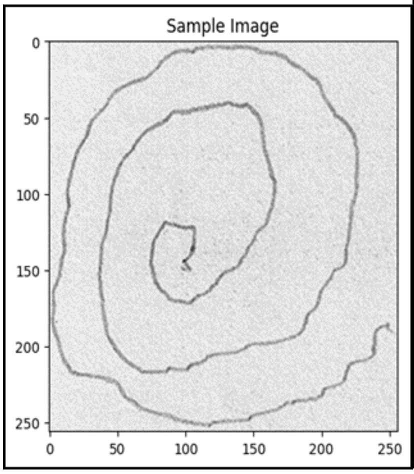


Figure 10 Healthy Image



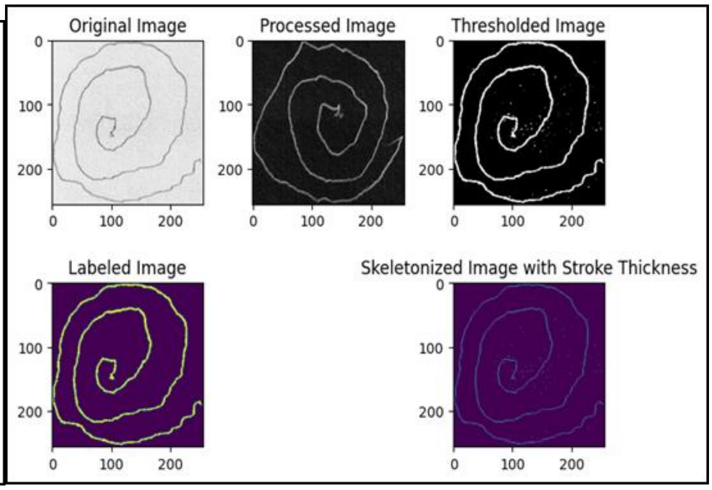


Figure 12 Parkinson's Image **Figure 13 Feature Extracted Image**

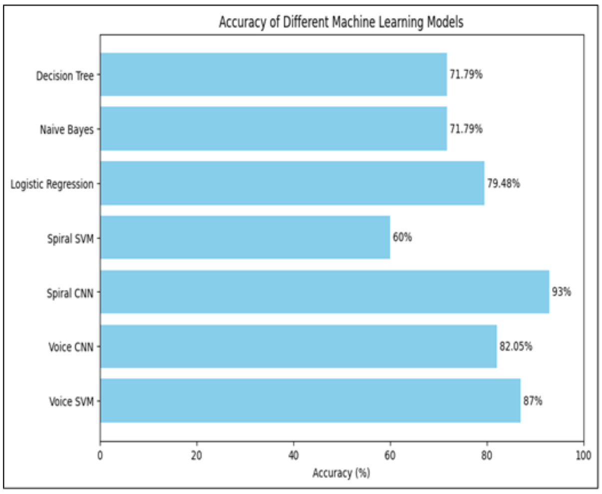


Figure 14 Bar graph indicating accuracy rates

Among traditional machine learning models, naive Bayes and logistic regression outperform decision trees in terms of voice data classification accuracy. SVM performs better on voice data than on spiral data, showing better sensitivity to data features. CNN outperforms traditional machine learning models, especially when processing complex data such as voice and spiral data. It is especially effective in voice data classification, with an accuracy of 82.03% compared to CNN, SVM and traditional machine learning models. Spiral object seems difficult for SVM as it only achieves 60% accuracy while CNN's accuracy is higher at 93%.

VII. DISCUSSION

The performance of SVM and CNN in many areas, such as voice data and spiral image data, is affected by the characteristics of the data and the algorithm itself. For voice data, SVMs are generally effective because they have high feature values and can handle data relationships. Voice data are often represented by high-dimensional feature vectors; where each feature corresponds to a different part of the speech signal, such as frequency components or spectrogram representations. SVM can divide the height of the surface into different classes, making them suitable for tasks such as speech recognition and classification. Additionally, voice data often has arbitrary decision boundaries, and SVM can effectively capture these boundaries using techniques such as kernel techniques. In contrast, CNNs may not perform well on speech objects because they are designed to learn representations of objects (e.g., images). Although speech data can be represented as spectrograms or other visualizations, it does not have the spatial structure that good CNNs use. Therefore, CNN may not be able to utilize its full hierarchical feature extraction capabilities for speech data, resulting in fewer features compared to SVM. For spiral data, CNNs perform well because they are specifically designed to learn hierarchical properties of spatial data. Spiral images, like other visual objects, have a relationship between pixels that captures important patterns and patterns. CNNs use convolutional layers to extract hierarchical features from image data, capturing low-level features such as edges and high-level features such as shape and texture. This algorithm makes CNNs efficient for tasks such as image classification and pattern recognition, including line detection in images. SVMs, on the other hand, may have problems handling convoluted data because they rely on identifying classes at a particular location. If objects have irregular relationships (such as spirals), SVM will have difficulty finding well-defined boundaries separating classes. SVM often requires architecture or the use of kernel methods to handle nonlinear data; this may not be as good as CNN's ability to learn hierarchical features directly from raw data. In summary, SVM is suitable for voice data due to its efficiency. CNN is good at processing highly spatial and temporal data, while CNN is good at processing convoluted data because they can learn hierarchical features of spatial data, which are important to capture. The patterns and patterns found in the spiral image are very important.

VIII. CONCLUSION

Parkinson's disease cannot be diagnosed directly; That is, a specific test such as a blood test or electrocardiogram cannot determine whether a person has Parkinson's disease. The doctor will take a detailed medical history of the patient and then perform a psychological examination. They identified at least two significant symptoms in the subjects and then predicted whether the patients had Parkinson's disease. The prognosis of PD is poor because there is no definitive diagnosis. In this case, it will help us assist doctors by providing machine learning models. Predictive models were developed for these key features using machine learning methods of support vector machines and convolutional neural networks. This article draws some conclusions. First of all, Parkinson's disease can be diagnosed using patterns and recording systems. Looking at the results, it can be seen that SVM and CNN models provide different accuracies for different data. On speech data, SVM is more accurate than CNN, while on spiral data, CNN is more accurate than SVM. From these results, we can conclude that CNN is more effective for images and SVM is better for registration.

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