

Parkinson's Disease Detection on Spiral Images Using CNN with Meta-Classifiers

S. Sumahasan¹, K. Purushotam Naidu^{2*}, V. Lakshmana Rao¹, A. Udaya Kumar¹

Abstract

In this work, we provide a detailed method for identifying Parkinson's Disease (PD) by integrating Convolutional Neural Network (CNN) and meta-classifiers. Through the utilization of a varied dataset consisting of handwritten spiral images, our methodology demonstrates commendable accuracy across a range of models. Specifically, our CNN model with meta-classifiers surpasses alternative approaches, achieving an impressive accuracy rate of 95.07%. By utilizing pre-established VGG16 and ResNet50 architectures as bases, the region-based CNN model achieves improved accuracy in PD detection, along with notable precision, recall, and f1-score evaluations. The results of this study emphasize the potential benefits of merging deep learning methodologies with ensemble techniques for reliable PD detection. Through the incorporation of CNNs with meta-classifiers, a hopeful route is introduced for non-invasive and precise identification of PD. This progress holds potential for enhancing patient outcomes and optimizing the efficacy of PD management protocols.

Keywords: Parkinson's disease, convolutional neural network (CNN), meta-classifiers, handwritten spiral images, VGG16, ResNet50

INTRODUCTION

Parkinson's disease, a neurodegenerative disorder that impairs motor function, highlights the necessity of early detection for effective treatment. Parkinson's disease (PD) is a major problem for both patients and healthcare providers due to its progressive nature and the complexities of symptom expression. Early identification is critical for effective management since timely intervention can dramatically enhance patient outcomes and quality of life. However, traditional diagnostic approaches sometimes rely on expensive and difficult-to-access imaging modalities, causing delays in diagnosis and treatment commencement [1, 2]. In response to this critical need, our initiative proposes a novel approach to Parkinson's detection that makes use of deep learning technology and patient-generated artwork. We hope to revolutionise the early detection of Parkinson's disease by analysing tiny motor anomalies captured in spiral and wave drawings, providing a non-invasive, cost-effective, and easily accessible solution for both patients and clinicians [3–5].

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Traditionally, the diagnosis of Parkinson's disease has relied mainly on clinical examination, augmented by neuroimaging techniques such as Magnetic Resonance Imaging (MRI) to visualise structural changes in the brain [1]. However, these technologies have considerable drawbacks, including high prices, restricted accessibility, and the inability to detect the subtle motor abnormalities that may appear in the early stages of the disease.

In response to these limitations, a game-changing method for Parkinson's detection has evolved, combining the power of patient-generated spiral and wave drawings with modern deep learning algorithms. By using the rich information buried in these drawings, our methodology overcomes the limitations of standard diagnostic methods, providing a non-invasive, cost-effective, and easily accessible method of detecting Parkinson's disease in its early stages.

Our approach is based on cutting-edge deep learning algorithms, such as Convolutional Neural Networks (CNNs) with Meta-Classifiers that use Logistic Regression and Random Forest, as well as Region-based Convolutional Neural Networks (RCNNs) that use VGG16 and RESNET50 architectures. These sophisticated models are trained to analyse the detailed patterns inherent in the drawings, identifying tiny motor anomalies that may serve as early indicators [2, 6].

This methodology aims to overcome the limits of existing diagnostic methods by integrating powerful deep learning models, such as Convolutional Neural Networks (CNNs) with Meta-Classifiers and Region-based CNNs, with cutting-edge architectures such as VGG16 and RESNET50. Using the detailed patterns in these drawings, our approach can precisely detect and localise important traits associated with Parkinson's disease, thereby improving diagnostic accuracy, and enabling proactive management.

This initiative marks a substantial leap in Parkinson's disease diagnosis, with the potential to alter how we detect and manage this terrible disorder. We hope to empower Parkinson's patients and their healthcare professionals by delivering a scalable and accessible solution that leverages the power of deep learning and patient-generated data.

LITERATURE SURVEY

The survey encompasses a range of studies, including reviews, systematic reviews, original research articles, and feasibility studies, to offer a thorough examination of the current landscape [2, 6, 7]. Key themes explored in the literature include the application of various deep learning models such as Convolutional Neural Networks (CNNs) and Region-based Convolutional Neural Networks (RCNNs) in analysing drawings for diagnostic purposes.

In the study, the researchers used machine learning techniques, specifically Convolutional Neural Networks (CNNs), to analyse drawing movements to detect Parkinson's disease early. The results showed high performance, with an accuracy rate of 85%.

The study investigate the efficiency of guided spiral drawing assignments for classifying Parkinson's disease [7–9]. The study used Spearman rank correlation coefficients to determine the relationship between various parameters. It hoped to identify variations between groups depending on Parkinson's disease severity levels by comparing several writing assignments.

The study used cross-validation and convolutional neural networks to detect Parkinson's disease in drawing movements. The study's results were outstanding, with an accuracy of 96.5%, an F1-score of 97.7%, and an area under the curve (AUC) of 99.2%.

The study used machine learning techniques such as Artificial Neural Network (ANN), K-Nearest Neighbours (KNN), and combinations of the two to predict Parkinson's disease. Specifically, combining KNN with AdaBoost.M1 and KNN with MLP resulted in 91.28% accuracy.

This work collectively demonstrates the efficacy of machine learning and neural network-based approaches in detecting and predicting Parkinson's disease, with high accuracy rates and the potential for early diagnosis and treatment.

PROPOSED SYSTEM

The suggested system includes two novel components intended at improving the accuracy of Parkinson's disease (PD) detection: a meta-classifier with Random Forest and Logistic Regression, and a region-based convolutional neural network (RCNN) using VGG16 and ResNet50 architectures.

Meta-classifier Using Random Forest and Logistic Regression

This component works with features extracted by a Convolutional Neural Network (CNN), a deep learning model noted for its performance in image analysis applications. The Meta-Classifier brings together the results of two complementary machine learning algorithms:

1. *Random forests*: Random Forest is well-known for its capacity to handle high-dimensional data and understand complex correlations between features. It is also effective at collecting nuanced patterns in data.
2. *Logistic regression*: It is a robust technique for binary classification tasks such as Parkinson's disease detection (distinguishing between the presence and absence of the disease). It gives a simple and interpretable method for classification.

This stage seeks to potentially improve classification accuracy beyond that of the CNN alone by using a voting mechanism in which both algorithms participate to the result.

Region-based Convolutional Neural Network (RCNN) with VGG16 and ResNet50

This component leverages the power of RCNNs to meticulously analyse distinct regions within handwriting samples, aiming to capture even more nuanced features relevant to PD classification. Pre-trained architectures such as VGG16 and ResNet50, renowned for their effectiveness in image recognition tasks, are employed (Figure 1).

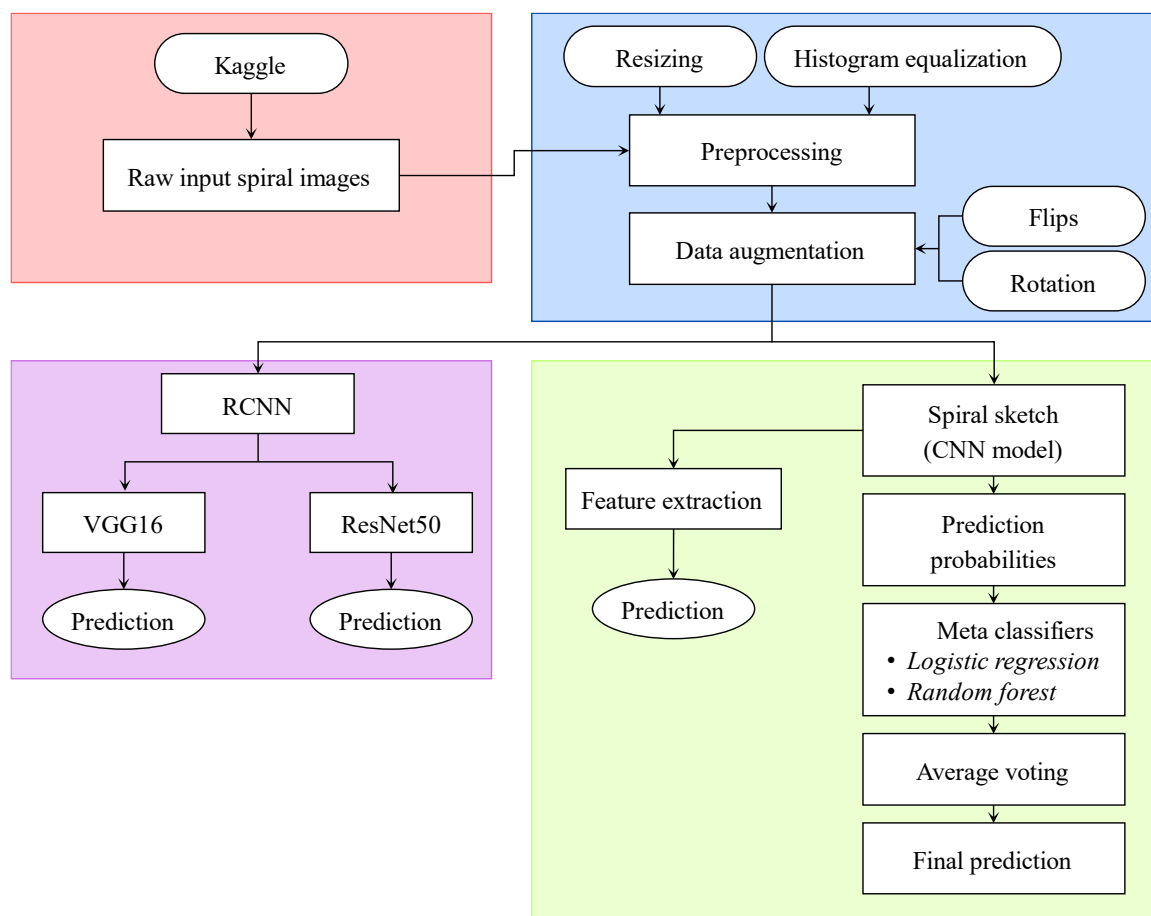


Figure 1. Workflow of the proposed system.

METHODOLOGY

This breakthrough technique to Parkinson's disease identification consists of many crucial components. Initially, patient-generated spiral and wave drawings are gathered and pre-processed, including scaling, normalisation, and augmentation, to standardise and improve the dataset's variability. Convolutional Neural Networks (CNNs) are then used to extract relevant characteristics from the drawings, taking use of their capacity to capture complicated patterns typical of Parkinson's illness. These collected features are then analysed by a Meta-Classifier that combines Logistic Regression and Random Forest methods. Logistic Regression excels in binary classification problems, whereas Random Forest is skilled at dealing with high-dimensional data and detecting complicated correlations between features.

A voting mechanism is used, allowing both algorithms to influence the final choice and potentially improving classification accuracy [10–12]. Concurrently, Region-based Convolutional Neural Networks (RCNNs) are used to methodically analyse specific sections of handwriting samples. Pre-trained architectures, such as VGG16 and ResNet50, which are well-known for their performance in image recognition tasks, are fine-tuned on the dataset to extract features from specific parts of the drawings.

The Meta-Classifier and RCNN-based models' outputs are combined to allow for more exact identification and localization of significant features in the drawings. The best-performing model is chosen using validation criteria such as accuracy, F1-score, and area under the curve (AUC). Finally, the validated model is used for non-invasive and easily accessible early detection of Parkinson's disease, allowing for prompt intervention and, eventually, better patient outcomes through early diagnosis and focused treatment regimens.

PARKINSON DETECTION

Introduction to CNN with Meta-Classifiers

The Meta-Classifier using Random Forest and Logistic Regression is a novel strategy for improving the classification accuracy of Convolutional Neural Networks (CNNs) in the context of Parkinson's disease detection. This Meta-Classifier, which uses features retrieved by the CNN from patient-generated drawings, combines the strengths of two complimentary machine learning algorithms: Random Forest and Logistic Regression. Random Forest excels at managing high-dimensional data and discovering complicated correlations between features, making it ideal for processing the CNN's rich and detailed information. Logistic Regression, on the other hand, is well-suited to binary classification problems such as determining the presence or absence of Parkinson's disease.

The Meta-Classifier uses a voting strategy in which both algorithms contribute to the final decision, aiming to capitalise on each algorithm's particular capabilities and perhaps enhance classification accuracy beyond what the CNN alone can achieve (Figure 2). This combination of classifiers enables a more comprehensive and nuanced analysis of retrieved data, ultimately improving the precision and reliability of Parkinson's disease identification.

Architecture

The architecture is made up of many convolutional layers, each followed by a pooling layer (Figure 3). Convolutional layers create feature maps by filtering the outputs of the previous layer. Pooling layers then minimise the size of the feature maps by summarising the data within them. Convolution and pooling allow the model to extract features from the input data.

The architecture also contains fully connected (FC) layers. These layers convert the features generated by the convolutional layers into a format that may be used by a classifier. The classifier may be a logistic regression model, a random forest model, or another sort of model. In the image, the meta-classifier is not mentioned.

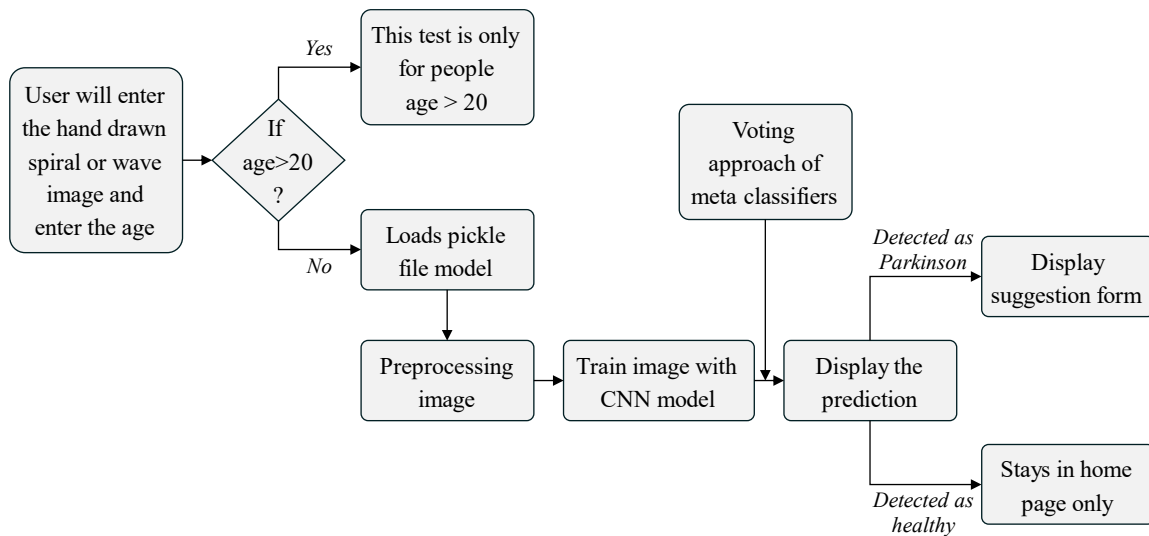


Figure 2. Workflow of the system.

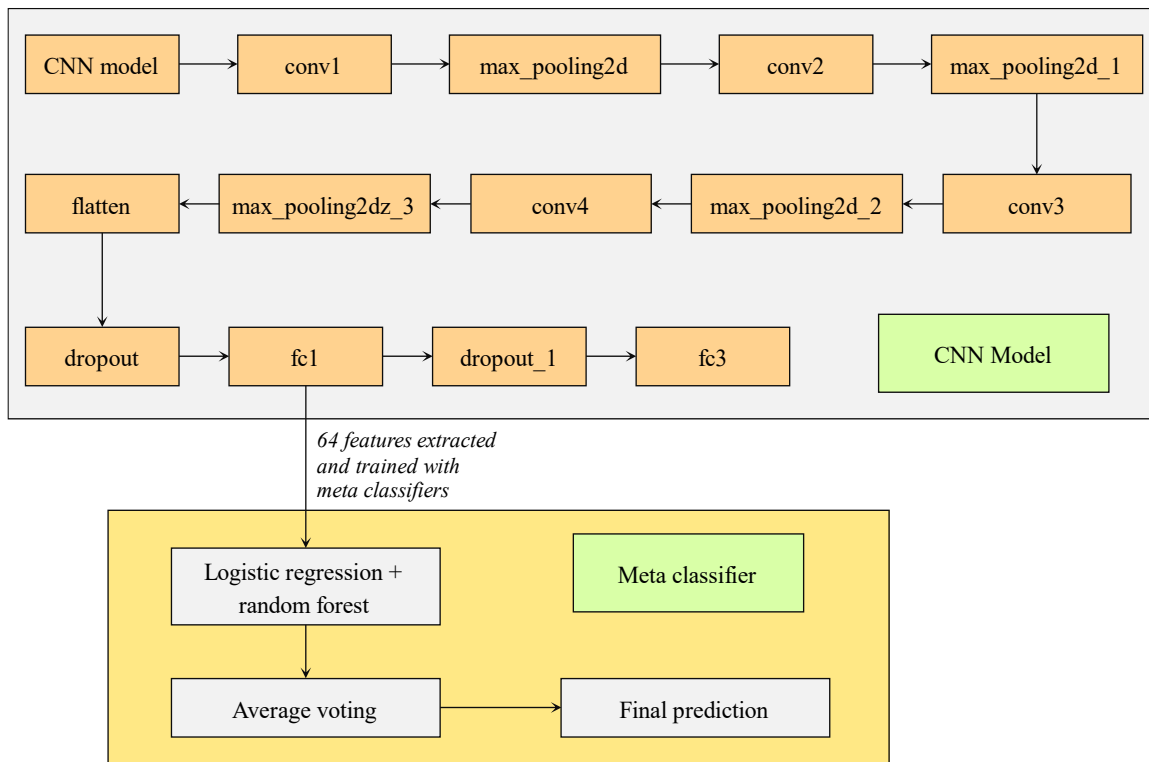


Figure 3. Architecture of CNN.

Training Procedure

Considering the provided spiral Parkinson’s dataset, alter the pre-trained model. In doing so, the model is customized to recognize the unique features of the spiral dataset. To improve model generalization, use data augmentation techniques (such as flipping, rotating, and colour jittering) to artificially expand the size of the dataset.

Make any adjustments to the pre-trained model using the supplied solar panel dataset [11–13]. By doing this, the model is adjusted to identify the distinct characteristics of the spiral dataset. Use data augmentation methods (such as flipping, rotating, and colour jittering) to intentionally increase the dataset’s size to enhance model generalization.

Data Preparation

During the data preparation phase, patient-generated spiral and wave drawings are gathered and pre-processed to ensure consistent and appropriate input for subsequent analysis. This starts with data gathering and organisation, followed by preprocessing techniques including image scaling, normalisation, and augmentation [14]. Image scaling ensures that image proportions are uniform, allowing neural network models to interpret data consistently. Normalisation is used to standardise pixel values across images, reducing variances in brightness and contrast that could impact model performance. Augmentation techniques, including as rotation, scaling, and flipping, are used to increase the dataset's variability and improve the model's capacity to generalise to new data.

These preprocessing processes are critical for preparing the dataset for feature extraction using Convolutional Neural Networks (CNNs) and subsequent analysis by the Meta-Classifier with Random Forest and Logistic Regression, assuring optimal performance and accuracy in Parkinson's disease identification.

Model Training

During the model training phase, the integrated approach of the Meta-Classifier with Random Forest and Logistic Regression, as well as the Region-based Convolutional Neural Network (RCNN) utilising VGG16 and ResNet50 architecture, is rigorously trained to improve its performance in detecting Parkinson's disease. After preprocessing, the patient-generated spiral and wave drawings are used as input data for the CNN, which extracts relevant features that capture modest motor impairments associated with Parkinson's disease [15, 16]. These features are then supplied into the Meta-Classifier, which trains Random Forest and Logistic Regression algorithms using the extracted feature set. Random Forest excels at handling high-dimensional data, whereas Logistic Regression is suitable for binary classification problems such as PD detection.

Through iterative training and validation, the Meta-Classifier learns to effectively combine the outputs of both algorithms using a voting mechanism, hence improving classification accuracy [17, 18]. Simultaneously, the RCNN is fine-tuned on a dataset of handwriting samples enriched for Parkinson's disease identification, utilising the capabilities of pre-trained VGG16 and ResNet50 architectures to extract nuanced information from specific regions of the drawings. This extensive training process guarantees that the model can precisely identify and localise significant elements within the drawings, resulting in precise and reliable Parkinson's disease identification.

Furthermore, because Parkinson's disease primarily affects people over 45 years old, the website hosting the model may include age verification measures to ensure that users are over the age of 20 years, as people in this age range are more likely to exhibit symptoms of the disease [18, 19]. This precaution helps to target the right demographic for screening and early detection efforts, increasing the model's value and relevance in clinical practice (Table 1).

Evaluation Metrics

The assessment measures for the built models (VGG16, ResNet50, and CNN with Meta-Classifiers) provide useful information on their performance in detecting Parkinson's disease. Precision, recall, F1-score, and accuracy are important measures for evaluating the effectiveness of classification models (Figures 4–6).

Table 1. Evaluation metrics.

Implemented models	Precision	Recall	F1-Score	Accuracy
VGG16	87	86	86	86
ResNet50	90	89	89	88.73
CNN with metaclassifiers	94.87	93.87	94.37	95.07

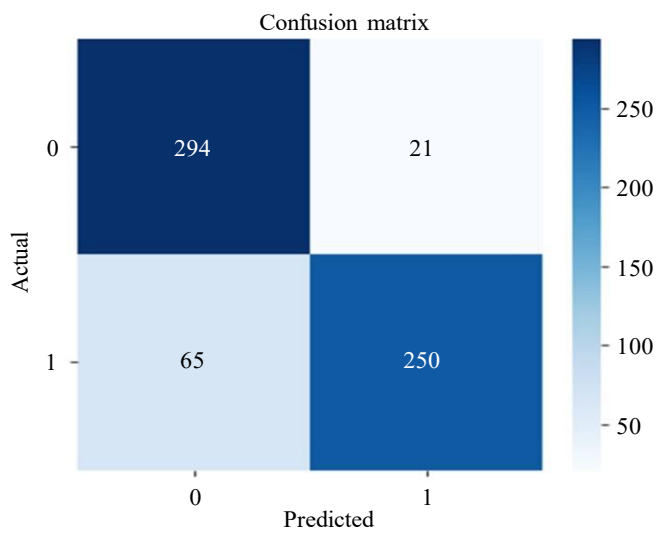


Figure 4. Confusion metrics of VGG16 model.

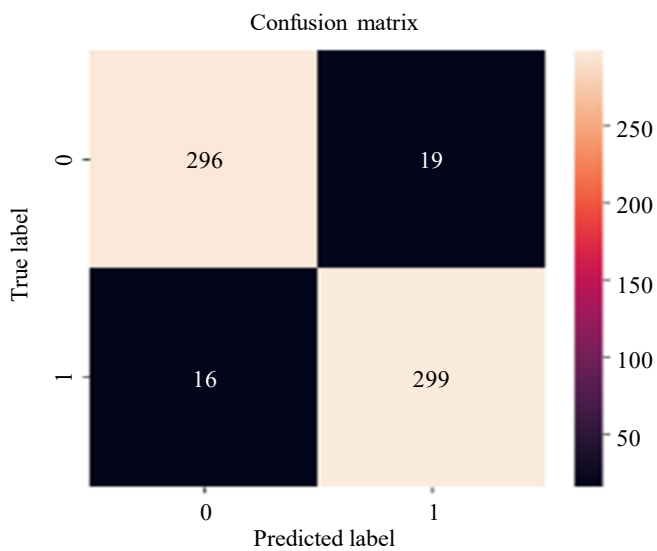


Figure 5. Confusion metrics of CNN with meta-classifiers.

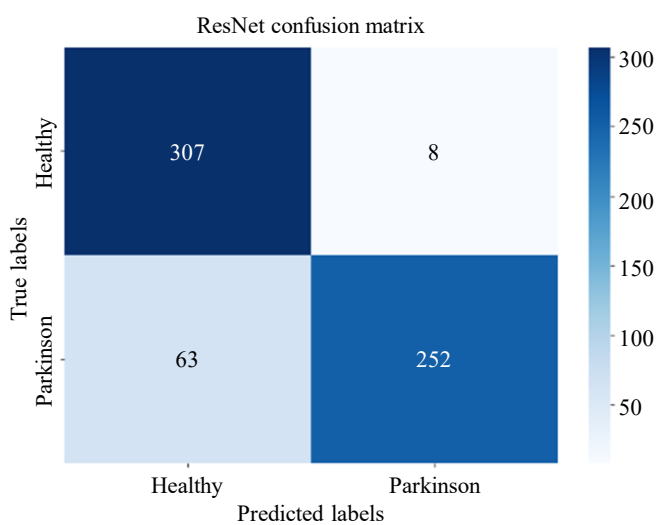


Figure 6. Confusion metrics of ResNet50.

RESULT AND ANALYSIS

The implemented models: VGG16, ResNet50, and CNN with Meta-Classifiers, show good results in predicting Parkinson's disease. However, when deploying the model on a public website, demographic and age-related parameters must be considered.

Given that Parkinson's disease primarily affects people over 45 years old, the website hosting the model should employ age verification methods to ensure that users are over the age of 20 years, as people in this age range are more likely to display signs of the disease. This precaution helps to target the right demographic for screening and early detection efforts, increasing the model's value and relevance in clinical practice.

When the model makes a prediction about the likelihood of Parkinson's disease, the website can launch a form or give the user with relevant information and suggestions. The form may include questions about the individual's symptoms, medical history, and other pertinent information to assist further evaluation and consultation with a healthcare expert.

The website can also include educational resources, support networks, and information about treatment alternatives for people impacted by Parkinson's disease [20, 21]. This holistic approach guarantees that consumers not only obtain accurate predictions, but also have access to comprehensive assistance and tools for optimal health management (Figures 7–9).

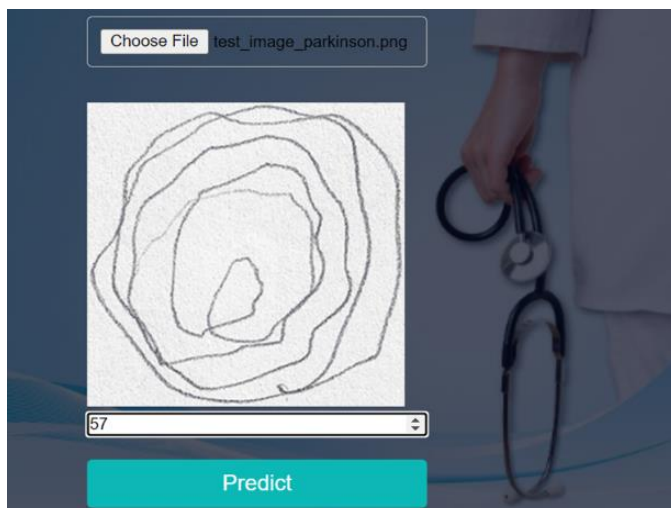


Figure 7. Spiral image uploaded by person with age 57.

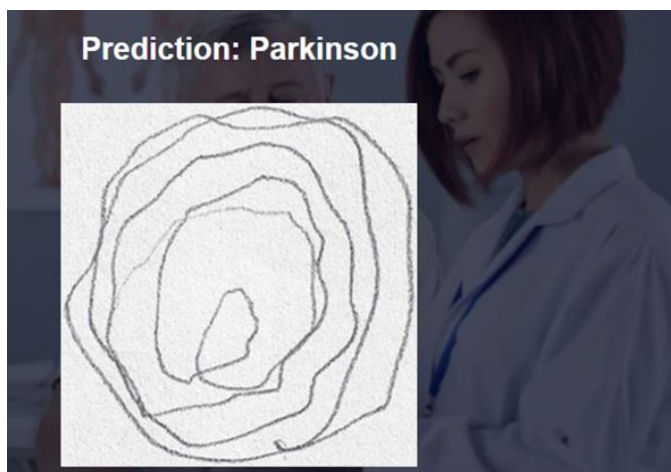


Figure 8. Parkinsons disease detection page.

Parkinson's Disease Risk Assessment

Age:

Gender:

Tremor: None Mild Moderate Severe

Memory Problems: None Mild Moderate Severe

Constipation: None Mild Moderate Severe

Depression: None Mild Moderate Severe

Hearing Loss: None Mild Moderate Severe

Loss of Smell: None Mild Moderate Severe

shaking: None Mild Moderate Severe

Dizziness: None Mild Moderate Severe

Fainting: None Mild Moderate Severe

Your risk of Parkinson's disease is low based on the provided information. However, it's essential to stay vigilant and consult a healthcare professional if you experience any concerning symptoms.

Your risk of Parkinson's disease is low. However, it's important to monitor any changes in symptoms and consult with a healthcare professional if you experience any concerns or new symptoms.

Note: Parkinson's disease risk increases with age, especially after 45 years old.

Figure 9. The Risk assessment for Parkinson Disease affected people.

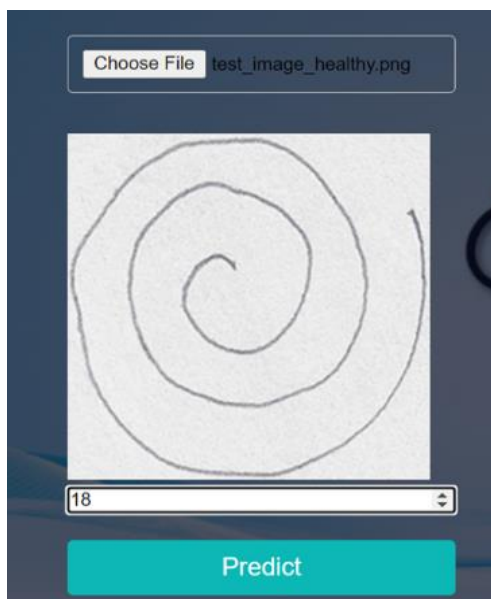


Figure 10. Spiral image upload by person with age 18 years.

Figures 10–12 give the implementation a user-friendly interface for image upload and displaying clear prediction results, the website can effectively facilitate early detection and management of Parkinson's disease, providing valuable support and resources to users. Figures 13 and 14 show us the output of the spiral images with the persons above 20 years old.

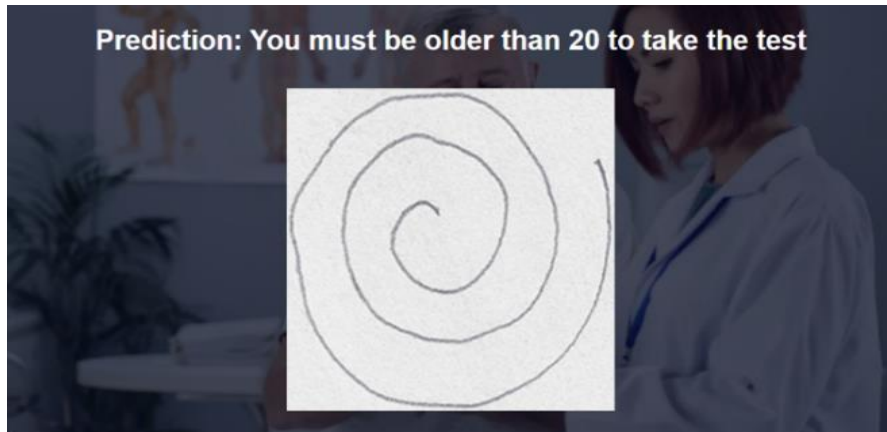


Figure 11. Below the age of 20 years cannot take the prediction test.



Figure 12. Person above the age 20 years with prediction.

Parkinson's Disease Risk Assessment

Age:

Gender:

Tremor: None Mild Moderate Severe

Memory Problems: None Mild Moderate Severe

Constipation: None Mild Moderate Severe

Depression: None Mild Moderate Severe

Hearing Loss: None Mild Moderate Severe

Figure 13. The Risk assessment form after Parkinson detection.

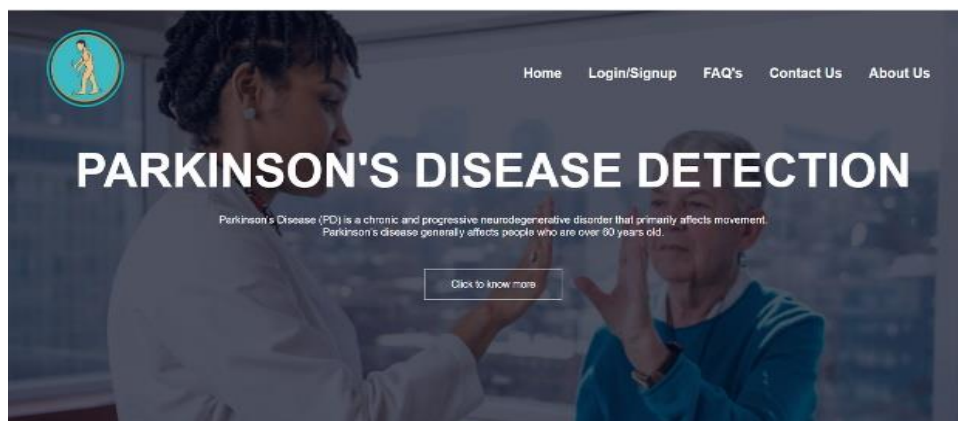


Figure 14. Website homepage.

CONCLUSION

In conclusion, the utilization of meta classifiers, including Random Forest and Logistic Regression, in conjunction with deep learning techniques for Parkinson's disease detection on spiral images represents a significant advancement in medical diagnostics. By leveraging sophisticated neural network architectures and large datasets, these methods have demonstrated promising results in accurately identifying patterns indicative of Parkinson's disease from hand-drawn spiral images. The integration of meta classifiers adds robustness and reliability to the detection process, enhancing the overall performance of the system.

The application of deep learning and meta classifiers in Parkinson's disease detection holds great potential for revolutionizing early diagnosis and intervention strategies. With further refinement and optimization, these techniques can contribute to improving the accuracy and efficiency of diagnosis, enabling healthcare professionals to identify the disease at its earliest stages. This enables timely interventions and the development of personalized treatment plans, leading to improved patient outcomes and enhanced quality of life.

Moreover, the scalability and flexibility of deep learning models enable their seamless integration into existing medical systems, facilitating widespread adoption and improved accessibility. By harnessing the power of advanced technologies, such as deep learning and meta classifiers, we can enhance the detection and management of Parkinson's disease, leading to better patient care and healthcare outcomes.

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