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PARKINSON'S DISEASE PREDICTION USING SPIRAL DRAWING IMAGE CLASSIFICATION USING IMPROVED VGG19

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Abstract

Motor symptoms greatly diminish the quality of life for those living with Parkinson's disease (PD), a degenerative neurological condition. An early and precise diagnosis is essential for treatment and therapy to be successful. Here, we see a state-of-the-art method for PD prediction based on spiral drawing picture categorization. The preprocessing stage utilizes the Enhanced Residual Noise Elimination Neural Network algorithm, substantially enhancing image quality by effectively reducing unwanted noise. The Improved Mask R-CNN is employed for segmentation, offering superior delineation of relevant structures within the spiral drawings. Feature extraction uses a Convolutional Neural Network (CNN) with AlexNet, which captures intricate patterns and essential details from the images. Finally, classification is performed using IVGG19 Networks, an architecture tailored explicitly for high-precision image classification tasks. Integrating these advanced techniques aims to improve the accuracy of Parkinson's disease prediction, providing a reliable tool for early diagnosis and aiding in better clinical decision-making.

Keywords: Improved Mask R-CNN, Image Segmentation, Parkinson's disease, Spiral Drawing, Image Classification

I. Introduction

Among the almost 600 disorders affecting the neurological system, Parkinson's disease (PD) stands out as a major international health issue, disproportionately impacting those aged 50 and over [1-3]. Motor functions are severely affected by this neurological illness, which leads to neuronal damage and manifests itself in tremors, stiffness, and brad-ykinesia [4-5]. In addition to motor symptoms, PD can cause various non-motor symptoms, such as problems with smell, anxiety, sleep, and vision [6]. Just as PD diagnostic tools, such as SPECT scans, which measure brain dopamine levels, are notoriously costly, patients also bear a disproportionate share of the financial burden, which compounds the social effect [7-9]. The WHO has named a group of neurodegenerative diseases as a significant public health concern. Diseases such as epilepsy, Parkinson's disease (PD), stroke, MS, headache problems, dementia, and a host of others are among the most prevalent conditions. Currently, neurological diseases are affecting an estimated 16 out of 60 persons [10–13].

Symptoms such as tremors, stiffness, bradykinesia, and postural instability are brought on by the primary impact of Parkinson's disease (PD) on motor processes [14–15]. Since no

treatment can reverse the illness's effects yet, getting a proper diagnosis as soon as possible is crucial for treatment planning and disease management [16–17]. Clinical evaluations have long been used for PD diagnosis, but they have limitations, including subjectivity and unpredictability. Because of this, there is a growing need for objective and automated early detection systems [18–19]. Analysis of spiral drawings, a simple yet efficient method for evaluating motor deficits, offers hope for diagnosing Parkinson's disease. One non-invasive way to identify the minor motor dysfunctions that diagnose PD is using spiral drawing tests, often used to measure tremor severity [20-21]. A new generation of automated systems can now analyze these designs and developments in computer vision and machine learning. This might lead to significant efficiency and accuracy gains. Using spiral drawing image categorization, this research introduces a new paradigm for predicting Parkinson's disease [22]. Improved diagnostic accuracy and reliability are the goals of the suggested method, which uses several state-of-the-art approaches [23–24]. The Enhanced Residual Noise Elimination Neural Network is used for preprocessing, and it efficiently reduces noise, which enhances the quality of spiral drawing pictures. Segmentation using the Improved Mask R-CNN improves structure delineation in these pictures by reliably capturing key features [25-26]. A CNN built on AlexNet is used for feature extraction since it excels at spotting complex picture patterns [27-28]. The last step in the classification process is the IVGG19 Networks, an architecture specifically developed for jobs requiring high accuracy in image categorization [29-31].
The main contribution of the paper is:

- Preprocessing using Enhanced Residual Noise Elimination Neural Network algorithm
- Segmentation using Improved Mask R-CNN
- Feature extraction using CNN with AlexNet
- Classification using Improved VGG19 Networks

What follows is an outline of the rest of the paper: Section 2 compiles the results of several studies examining different ways to diagnose Parkinson's disease (PD). In Section 3, we see the model and its execution. The investigation's findings are summarized in Section 4. Section 5 concludes with a discussion of the results and an overview of future research prospects.

1.1 Motivation of the paper

To improve patient outcomes and enable effective therapy, an early and precise diagnosis of Parkinson's disease (PD) is essential. The subjective nature of traditional diagnostic procedures raises the possibility that they miss minor, early indications. One potential way to improve diagnosis accuracy is to use state-of-the-art image processing and machine learning methods. The need to create a dependable automated system for Parkinson's disease prediction utilizing spiral drawing images—simple but illuminating of motor impairments—motivates this work. This approach seeks to improve patient care and management of PD by integrating state-of-the-art techniques such as Enhanced Residual Noise Elimination Neural Network for image quality improvement, Improved Mask R-CNN for precise segmentation, CNN with AlexNet for detailed feature extraction, and IVGG19 Networks for high-precision classification. We aim to provide a robust tool for early diagnosis and better clinical decision-making.

II. Background study

Ali, S. et al. [1] The possibility of handwriting characteristics as PD predictors was shown in this research. Kinematic, spatio-temporal, and pressure characteristics have been the subject of literary investigation. Nevertheless, this research finds that GRU achieves the highest accuracy when combining online and offline information with various classifiers, including one-dimensional Convolution, LSTM, and RNN. The research on online features was not denied in this study.

Alshammri R. et al. [3] the author suggested a method that uses aspects of speech signals in conjunction with machine learning and deep learning to detect Parkinson's disease. Results obtained using these approaches outperform those of earlier research. Through the timely provision of early diagnoses, the suggested operational model can contribute to the reduction of treatment expenses. There were a lot of ways this prediction model might be enhanced to make it more accurate and more scalable.

Jain, D. et al. [8], the research goal of these authors was to provide techniques for automated Parkinson's disease prediction using several ML algorithms. According to the experimental data, ensemble learners were generally effective in predicting whether the illness was present. Improving the DNN-based technique for this prediction problem via appropriate oversampling has also been noted.

Mary, G., & Suganthi, N. [12] by merging Darknet 19 with CNN, this work introduces a new method for image classification. It was difficult to diagnose Parkinson's disease at an early stage. MFEA used several ranking and feature evaluation algorithms to select the best set of features by giving each feature a relative value. The classifier's performance was enhanced when features were selected using principal component analysis.

Siuly, S. et al. [23] The primary aims of this study were to find the region of the brain that provides crucial information for accurate PD diagnosis using EEG data and improving the efficacy of the proposed approach relative to existing techniques. In order to do this, a CNN framework based on TFR was created for PD diagnosis using EEG.

Table 1: Comparison of Methodologies for Parkinson's disease Detection

Author	Year	Methodology	Advantage	Limitation
Ali et al.	2023	C-Bi-GRU and VGG19	Combines dynamic and static features for improved assessment accuracy	Limited to handwriting data; cannot generalize to other motor symptoms or datasets
Almeida et al.	2019	Machine learning	Effective in utilizing speech features for disease detection; non-invasive method	Reliance on speech data, which can vary significantly across individuals
Chakraborty et al.	2020	Convolutional neural networks	The multi-stage classifier approach improves detection accuracy	Can require large and diverse dataset to achieve high performance across

				all cases
Kaur et al.	2021	Deep CNN	Utilizes transfer learning and data augmentation to enhance model robustness	Requires extensive computational resources for training deep models
Siuly et al.	2024	Time-frequency representation combined with AlexNet CNN	Integrates time-frequency analysis with deep learning for accurate detection	It can be complex to implement and require significant preprocessing of data

2.1 Problem definition

The early signs of PD are vague and not always specific, making diagnosis difficult. It is possible that traditional diagnostic procedures do not fulfill the sensitivity and accuracy needed for early detection. To address this issue, a more accurate method of diagnosing Parkinson's disease is required. This study addresses that gap by developing a cutting-edge approach for picture classification that relies on spiral drawings. Noise reduction, precise segmentation, comprehensive feature extraction, and high-precision classification are all part of the proposed technique, which aims to improve diagnostic accuracy and provide an automated tool for early Alzheimer's disease detection.

III. Materials and methods

Here we provide the suggested approaches for PD prediction using spiral drawing picture categorization. The procedure starts with preprocessing using the ERNEN algorithm to improve picture quality and decrease noise. In order to properly demarcate important structures within the pictures, the Improved Mask R-CNN (I-Mask R-CNN) is used for segmentation. The rich patterns and details from the spiral paintings are captured using a CNN utilizing AlexNet during feature extraction. In the end, Parkinson's disease is predicted by classification using IVGG19 Networks, a state-of-the-art architecture developed for very accurate picture categorization.

3.1 Dataset collection

The dataset used in this study was obtained from the Kaggle website, specifically from the repository available at https://www.kaggle.com/datasets/team-ai/parkinson-disease-spiral-drawings. This dataset comprises a collection of spiral drawing images used to analyze and predict PD. The dataset includes various images of spiral drawings produced by individuals with and without Parkinson's disease, providing a valuable resource for training and evaluating the proposed image classification models.

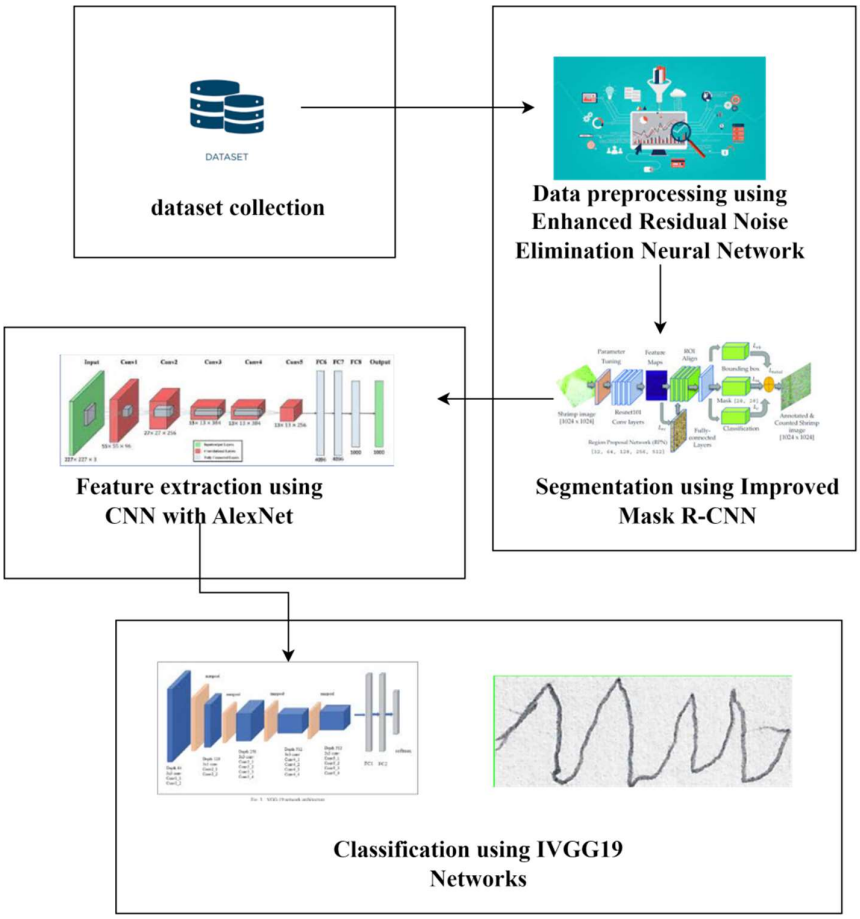

Figure 1: Proposed workflow architecture

3.2 Data Preprocessing using Enhanced Residual Noise Elimination Neural Network

In order to preprocess spiral drawing pictures, the Enhanced Residual Noise Elimination Neural Network (ERNEN) is used. This network employs sophisticated noise reduction methods to improve the images' quality dramatically. Using residual learning improves picture clarity, reducing noise while keeping crucial structural features intact. The accuracy and reliability of predictions for Parkinson's disease diagnosis are enhanced by preprocessing using ERNEN, which assures that the two stages of image analysis—segmentation and feature extraction—operate on high-quality, noise-free data.

Before using the Denoising Convolutional Neural Network, we obtained a picture with Gaussian noise using the median filtering procedure. When dealing with Gaussian noise, which is often represented as a single noisy level image, ERNEN residual learning and batch normalization capabilities allow for rapidly acquiring a noise-free image. As a result, we ran ERNEN through its denoising process once again, this time with the parameters shown below.

Through end-to-end deep convolutional neural network residual learning, a latent clean picture was acquired by means of which Gaussian noise was substantially reduced. An example of a noisy ERNEN observation is the image y = x + v, which contains Gaussian noise.

Efficiency and effectiveness of Convolutional Neural Network training on noise-free images by batch normalization and residual learning

There are no pooling layers in the network and its depth D is$d_{i,j}$. The convolutional

filter size is 3 × 3.

$B = |\sum_{i=1}^{q}(\sum_{i=1}^{q} f_{i,j} d_{i,j})|$ ---------- (1)

In this case, q is the size of the window, $f_{i,j}$ is the coefficient of the convolutional window at position i, j, $d_{i,j}$ is the value of a pixel convolved with $f_{i,j}$ and B is the result of the convolutional

$f_{i,j} = \frac{w - f_{i-1,j-1} + 2P}{s} + 1 \times \frac{h - f_{i-1,j-1} + 2P}{s} + 1$ ---------- (2)

As the previous window size is represented by $j - 1$, and p and s are the padding and stride of the filters$fi - 1$,

To increase the model's accuracy and prevent overfitting during training, L2 regularization is used.

$Loss = Error(A, B) + y \sum_{i=1}^{N} w_i^2$ ---------- (3)

The L2 regularization coefficient, denoted $\sum_{i=1}^{N} w_i^2$ determines the appropriate coefficient by means of iterative updates conducted using optimizer algorithms. In order to identify and analyze the green, blue, and red channels, channel selection is used. The noisy and noise-free channel pixels are identified in the conditional section. A new, better median filter eliminates salt and pepper noise. In the end, a convolutional neural network can clean up input images by filtering out Gaussian noise.

3.3 Segmentation using Improved Mask R-CNN

Improved segmentation accuracy and precision are the results of this cutting-edge method, which expands upon the Mask R-CNN architecture. To reliably extract features and classify them for Parkinson's disease prediction, the Improved Mask R-CNN effectively distinguishes between various regions and features in the spiral drawings, isolating and identifying critical details.

Improved Mask R-CNN uses a combination of losses to accomplish its multitasking goals. These losses include the following: $L_{Bbox_{RPN}}$ for objectness region extraction, class loss $L_{clas\ _{RPN}}$ for objectness region classification, L_{Mask} for object segmentation, and L_{Class} for objectness region extraction in the RPN subnet.

$Loss_{total} = L_{class_{RPN}} + L_{Bbox_{RPN}} + aL_{Class} + \beta L_{Bbox} + L_{Mask}$ ---------- (4)

Improved Mask R-CNN achieves multitask learning by experimentally setting the hyper-parameters α and β to 1 and concurrently minimizing all losses, even though different losses can produce different degrees of learning. For example, network parameter updating would benefit much from a loss function with a big value, whereas network learning would not benefit much from one with a lower value. We have found that RPN losses often do not significantly impact the final prediction outcomes since their primary function is to help get the first object candidates that are sent to the next prediction step. Given that classification, segmentation, and bounding box regression are all affected by the three losses in different ways, a lower value for one loss might provide insufficient learning for its respective job, which could have a negative impact on the other two.

$a_{t+1} = \frac{max(L_{class}, L_{Bbox}, L_{Mask})}{L_{Class}} a_t$ --------- (5)

$\beta_{t+1} = \frac{max(L_{Class}, L_{Bbox}, L_{Mask})}{L_{Bbox}} \beta_t$ ---------- (6)

$Loss_{totalt+1} = L_{ClassRPN} + L_{BboxRPN} + a_{t+1}L_{Class} + \beta_{t+1}L_{Bbox} + L_{Mask}$ ---------- (7)

A weight at the t[th] epoch is represented by a_{t+1}, while an updated weight at the $(t + 1)^{th}$ epoch is a_{t+1}. At the beginning of the network training operation, we set the starting weights at $\alpha 1 = 1$ and β_{t+1}, and we update them at each epoch.

The wide range of features seen in microscope images—including size, shape, appearance, staining, and texture—makes it difficult to detect and identify some cells relative to others. In place of cross entropy loss, we use improved Mask R-CNN with focused loss for object classification. Focused loss reduces the impact of losses from many weak samples by focusing on a small number of difficult samples. As a result, we can raise the loss for nuclei that are difficult to see in micrographs and lower it for nuclei that are easy to see. One way to indicate the concentrated loss that this training sample produces is by using the symbol P_T to represent the projected probability on the ground truth class T.

$L_{Focal\ Loss} = -\delta(1 - P_T)^{\gamma} logP_T$ -------- (8)

Hyper-parameters δ and γ are used to modulate the overall loss and the individual cell losses, respectively, in relation to the classification complexity. For this research, we assumed that γ = 1. As a result, the object classification task's learning degree would be diminished in comparison to other tasks. So, to construct the hyper-parameter δ in a way that balances the focal loss with other losses, we provide an automated regulating technique.

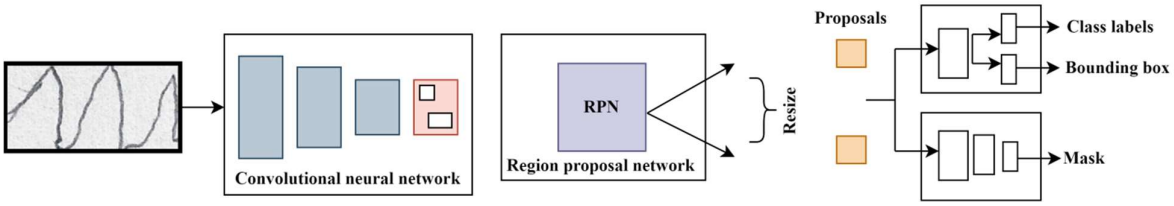

Figure 2: Improved mask R-CNN architecture

3.4 Feature extraction using CNN with AlexNet

CNNs trained on AlexNet are used for feature extraction because of their exceptional ability to pick up intricate features and patterns in spiral drawing pictures. AlexNet is able to learn and successfully extract complex information from pictures because of its deep architecture, which includes many convolutional layers and pooling processes. More accurate and useful classification findings can be achieved by improving the capacity to detect small PD-related alterations and traits.

One subfield of deep learning that has seen a lot of research and practical use is the CNN. This model is an enhancement to the BP neural network and a multi-layer network in general. All of them employ forward propagation to send computed values out into the world, and back propagation to tweak their biases and weights. CNNs differ from conventional recognition algorithms in that they immediately output their findings via the complete connection after continuously using the convolution and pooling operations on the original input to build more complicated feature graphs. The input, convolution, pooling, full connection, and output layers make up its key components.

To make Alexnet faster and more accurate, the author employed the ReLU activation function in conjunction with Dropout. Formula (9) defines the ReLU activation function, which

is shown in Figure 3. In terms of network convergence speed, this activation function outperforms Sigmoid and Tanh. It offers great computational efficiency and can prevent the gradient vanishing issue. It is possible that neurons can die off during training if we apply the ReLU activation function, rendering it unable to update the weight. Assuming that occurs, the gradient passing through the neuron from this point forward will perpetually be zero.

$$f(y) = \begin{cases} y, & if\ y > 0 \\ 0, & if\ y \leq 0 \end{cases} \text{ ---------- (9)}$$

Formula (2) shows the definition of PReLU, a novel nonlinear corrective activation function. When it comes to convergence, PReLU is quicker than ReLU. Overfitting is not a major concern for PReLU, even if it adds an additional parameter "a". On top of that, by using back propagation to learn "a" updates, neurons can choose the optimal gradient in the negative area. So, to activate Alexnet, we utilize PReLU in this post.

$$f(y) = \begin{cases} y_i, & if y_i > 0 \\ a_i\ y_i, & if\ y_i \leq 0 \end{cases} \text{ -------- (10)}$$

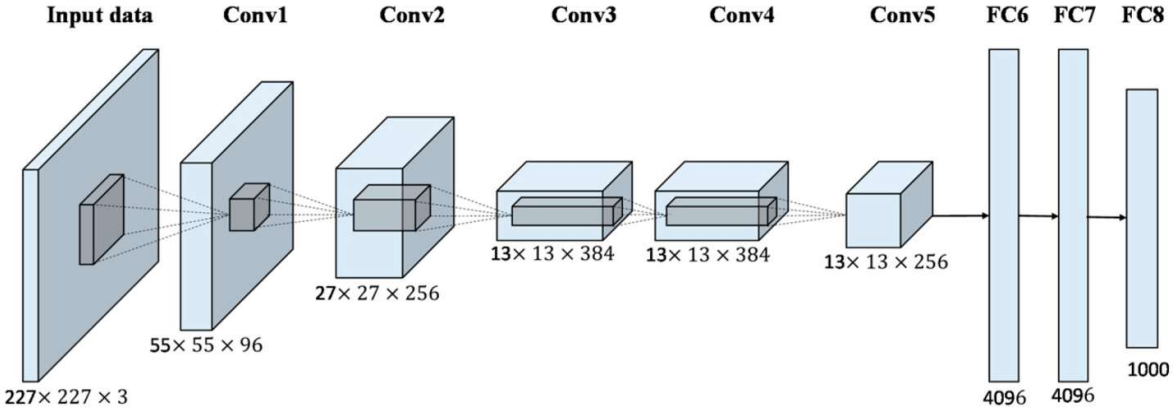

Figure 3: CNN with Alexnet architecture

3.5 Classification using IVGG19 Networks

Cutting-edge image classification architecture developed for tasks demanding high accuracy, IVGG19 Networks are used for categorization. IVGG19 is an upgrade to the VGG19 model that improves its ability to differentiate between various picture classes. Through the use of its deep learning skills, this network can reliably diagnose Parkinson's disease by processing and classifying characteristics taken from spiral drawing pictures.

Every one of a VGG CNN's six main parts is essentially a network of many linked convolutional and full-connected layers. A 224*224*3 input is used with a 3*3 convolutional kernel. In most cases, 16–19 layers are tightly packed. Figure 1 shows the structure of the IVGG-19 model.

By combining many convolutional and non-linear activation layers, it achieves better results than utilizing just one. The layer structure improves feature extraction from images by downsampling using Maxpooling and replacing the linear unit (ReLU) with a modified version. Put another way, it can take the area's pooled value as its maximum value inside the picture region. This enhances the network's capacity to prevent visual distortion. First, here is the expression of the downsampling layer: (1).

$$x_{p_j}^{(n)} = f\left(\tau_j^n dwon\left(x_j^{(n-1)}\right) + b_j^{(n)}\right) \text{ ---------- (11)}$$

Conventional detection systems struggle to handle the aforementioned problems due to the wide range of mask colors, scene states, and variations in the lighting conditions of the workplace. This optimizes the model parameters of the convolution layer. All of IVGG-19's parameters are located in only three FC layers. This article primarily covers the categorization of two categories (if wearing masks), however the network parameters were initially planned for a thousand classifications. A 2-label Softmax classifier takes the place of the original layer, and sparse features are made use of by means of Dropout and Max pooling.

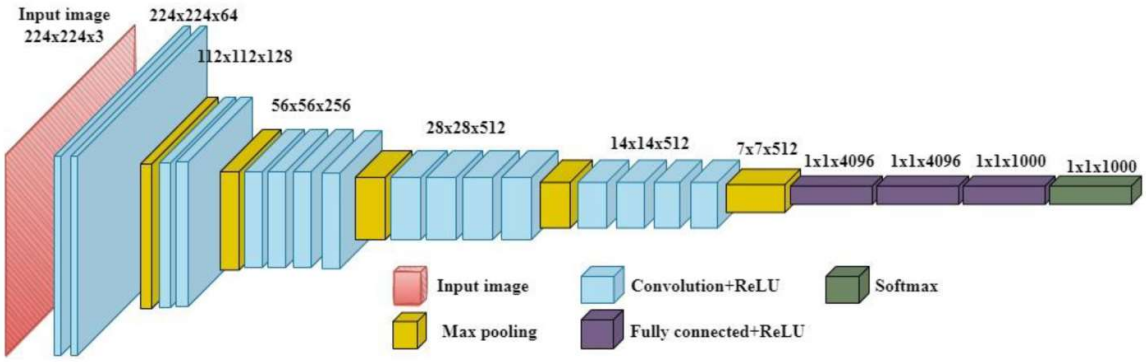

Figure 4: Improved VGG 19 architecture

Algorithm 1: Improved VGG19 Networks

Input:

1. **Spiral Drawing Images**: Preprocessed images of spiral drawings, each resized to 224x224 pixels with 3 color channels (RGB). These images are used as input to the IVGG19 network.

Steps:

- Resize the input spiral drawing images to 224x224 pixels.
- Normalize pixel values to a range suitable for the VGG19 network

  Convolutional Layers: Hierarchical features are extracted from input pictures by means of the network's application of several convolutional layers equipped with 3x3 kernels.
- **Activation Function**: Use ReLU activation after each convolutional layer to introduce non-linearity.

  $y = f(W * x + b)$

  where W represents the convolutional kernel, x the input image, b the bias, and f the activation function (ReLU).

  Max Pooling: Retain the most important features after downsampling the feature maps by using max pooling.

 Classification:

- **Flatten Layer**: Convert the 3D feature maps into 1D vectors
- **Fully Connected Layers**: Pass the flattened vectors through fully connected (dense) layers.

Output:

1. **Class Labels**: The classification results output by the IVGG19 network, indicating whether the image corresponds to a PD or non-Parkinson's Disease (non-PD) category.

IV. Results and discussion

Presenting and evaluating the data obtained from our study, we assess the efficacy of many models in predicting Parkinson's disease using spiral drawing picture classification. We evaluate the efficacy of different methods using crucial performance metrics such as Accuracy, Precision, Recall, and F-measure. This study shows how each model performs and where it falls short, giving us a better idea of which one is most suited to the job. The purpose of this discussion is to analyze the results by looking at what they mean for clinical application and early diagnosis.

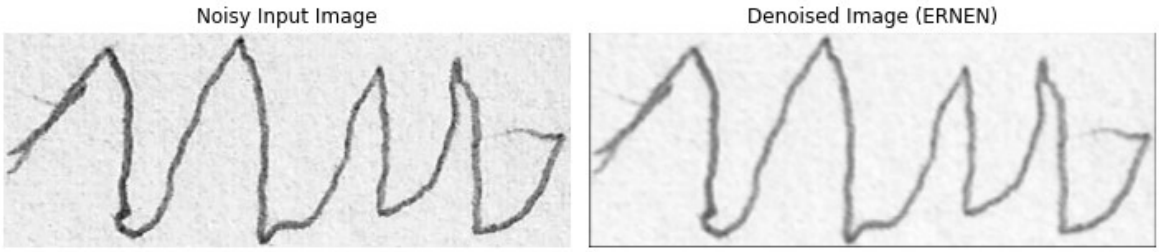

Figure 5: Denoised image

Figure 5 illustrates the results of the denoising process applied to spiral drawing images used for Parkinson's Disease prediction. The figure presents three examples of denoised images processed using different denoising techniques: Enhanced Residual Noise Elimination Neural Network (ERNEN).

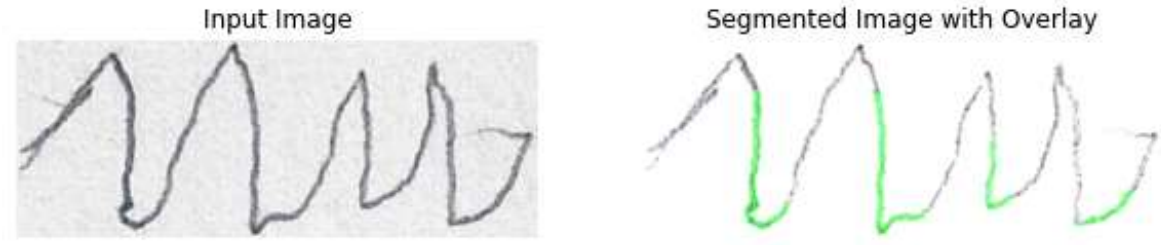

Figure 6: Segmented image with overlay

Figure 6 presents the segmented images with an overlay that is used to analyze spiral drawing images in the context of Parkinson's disease prediction. This figure visually demonstrates the segmentation process, highlighting the delineation of key features within the images.

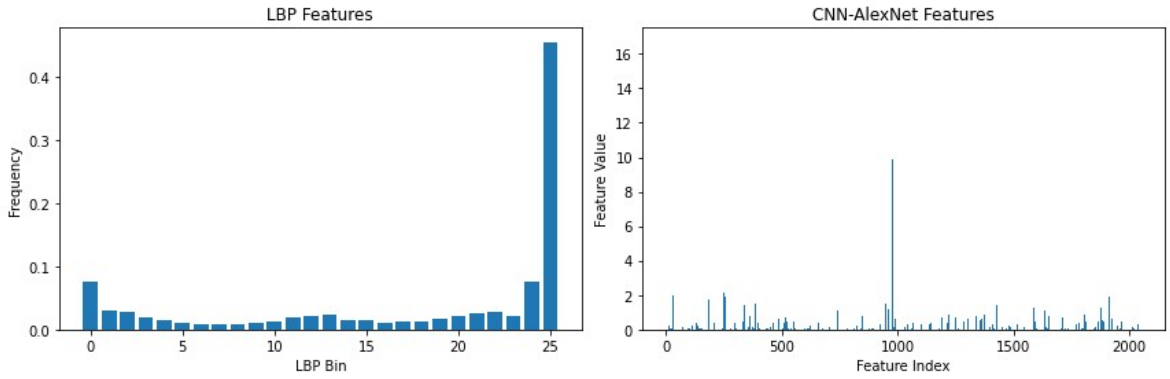

Figure 7: Feature importance

Figure 7 shows how important features are when using spiral drawings to forecast the onset of Parkinson's disease. The importance of the picture characteristics that go into the prediction model as a whole is graphically shown in this figure.

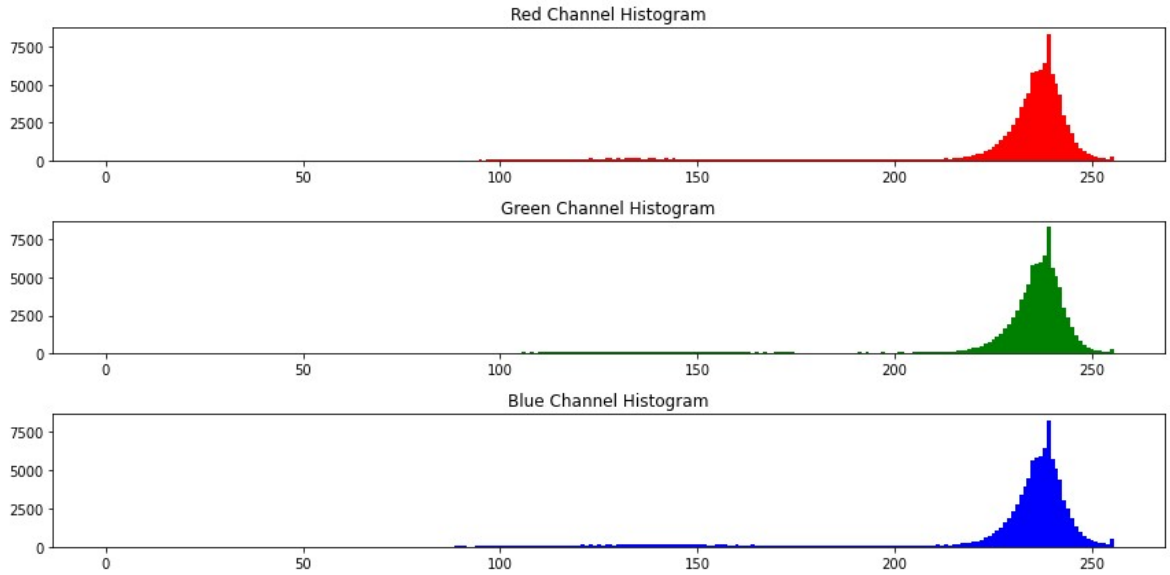

Figure 8: Red, green, and blue channel histogram

Figure 8 presents the histograms of the Red, Green, and Blue (RGB) channels for the spiral drawing images used in Parkinson's Disease prediction. This figure offers a detailed analysis of the color distribution across each channel, providing insights into the color characteristics of the images that might be relevant for the classification task.

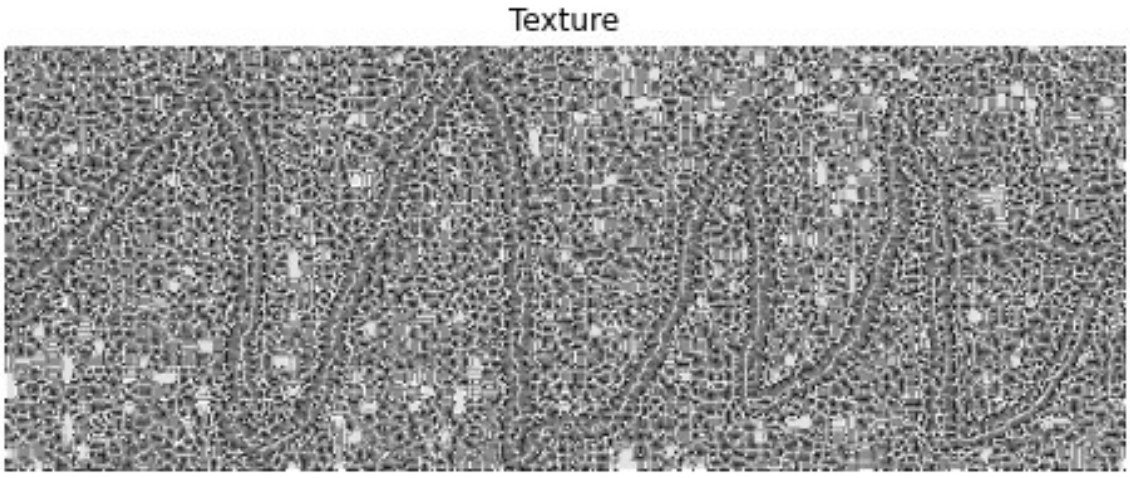

Figure 9: Texture

Figure 9 illustrates the texture analysis of the spiral drawing images used for Parkinson's Disease prediction. This figure provides a visual representation of the textural features present in the images, which play a crucial role in differentiating between various patterns and structures relevant to disease diagnosis.

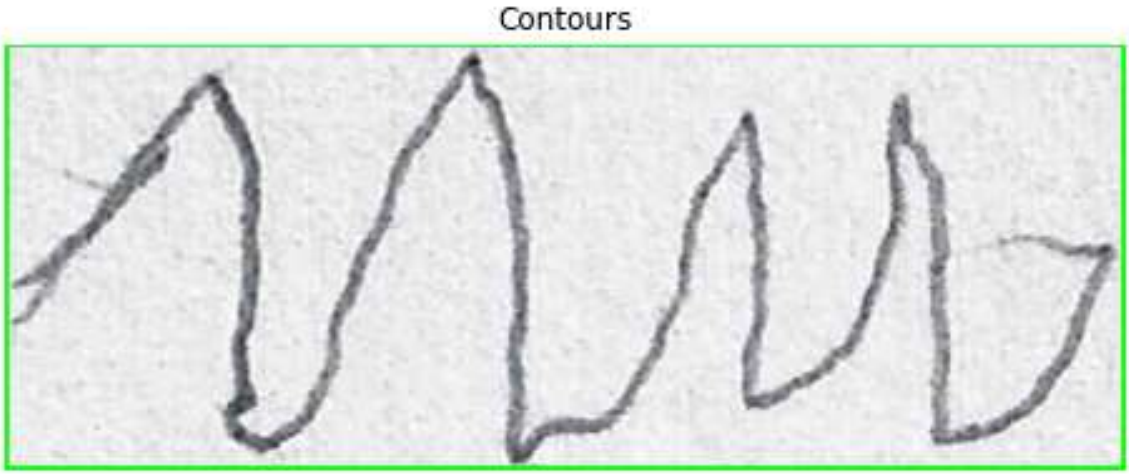

Figure 10: Contours

Figure 10 displays the contour detection results applied to the spiral drawing images used for Parkinson's Disease prediction. Contour detection is a vital image processing technique that helps identify the boundaries and shapes within an image, which are essential for accurate feature extraction and subsequent classification.

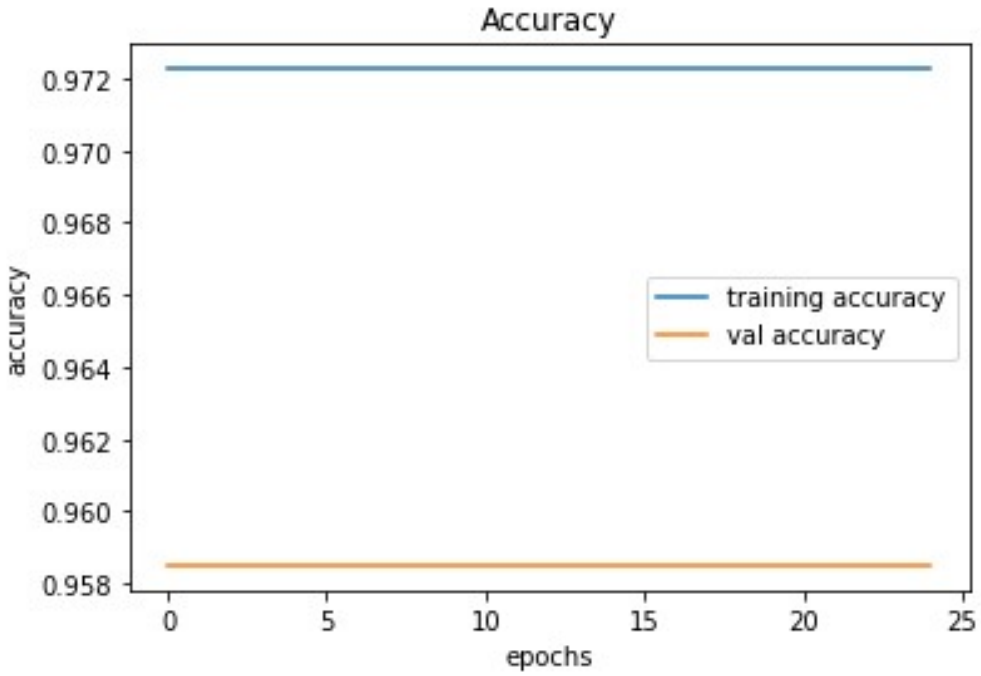

Figure 11: Training accuracy value comparison chart

Figure 11 displays a chart comparing training accuracy values. Values for precision are shown on the y-axis and epochs are shown on the x-axis.

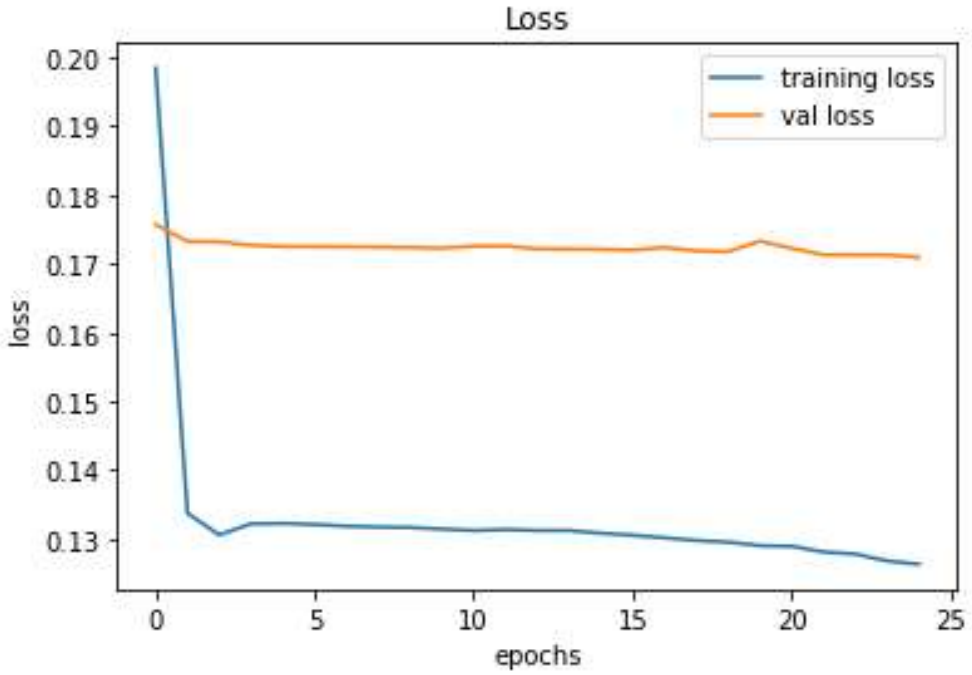

Figure 12: Training loss value comparison chart

A comparison chart of training loss values is shown in figure 12. Epochs are shown on the x-axis, while training loss is shown on the y-axis.

Table 2: Denoising value comparison table on PD

	Denoising value comparison on PD			
NLM [30]		PSNR	SSIM	RMSE
	100.jpg	8.11	0.78	0.47
	101.jpg	8.21	0.78	0.44
NLW [31]	100.jpg	8.62	0.79	0.43
	101.jpg	8.91	0.82	0.41
ERNEN	100.jpg	9.20	0.85	0.37
	101.jpg	9.24	0.87	0.34

The table 2 comparison of denoising algorithms for Parkinson's Disease (PD) image processing reveals notable differences across three metrics: PSNR, SSIM, and RMSE. For PSNR, which measures image quality after denoising, the Enhanced Residual Noise Elimination Neural Network (ERNEN) outperforms both the Non-Local Means (NLM) and Non-Local Wavelet (NLW) methods. Specifically, ERNEN achieved PSNR values of 9.20 and 9.24 for images 100.jpg and 101.jpg, respectively, compared to NLM's 8.11 and 8.21 and NLW's 8.62 and 8.91. In terms of SSIM, which assesses image structural similarity, ERNEN again excels with SSIM scores of 0.85 and 0.87, significantly higher than NLM's consistent 0.78 and NLW's 0.79 and 0.82. Lastly, for RMSE, which indicates the amount of residual noise, ERNEN shows the lowest values, 0.37 and 0.34, highlighting its superior denoising capability compared to NLM (0.47 and 0.44) and NLW (0.43 and 0.41). Overall, ERNEN demonstrates the highest performance across all metrics, suggesting it provides the best image quality enhancement for PD image processing.

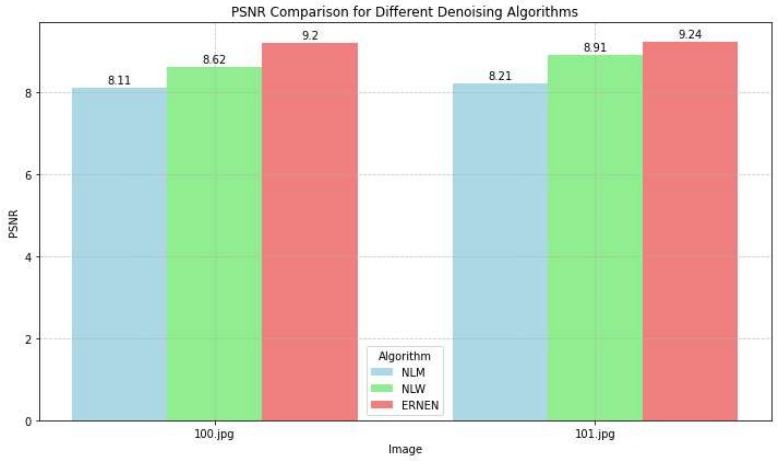

Figure 13: PSNR value comparison chart

The figure 13 shows PSNR value comparison chart the x axis shows image and the y axis shows PSNR value.

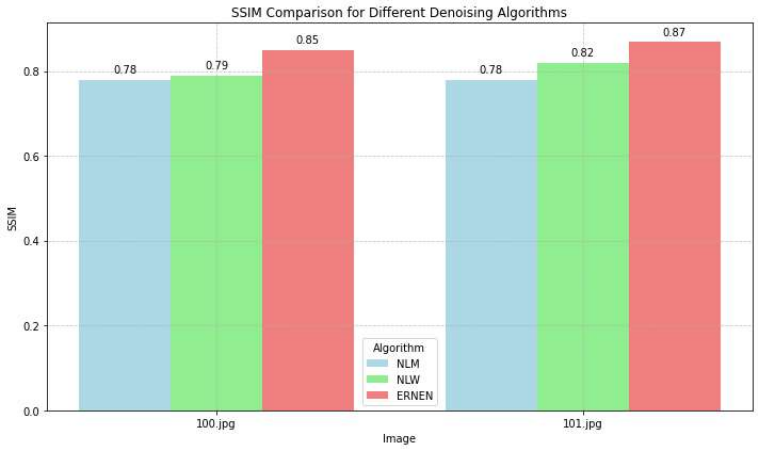

Figure 14: SSIM value comparison chart

The figure 14 shows SSIM value comparison chart the x axis shows image and the y axis shows SSIM values.

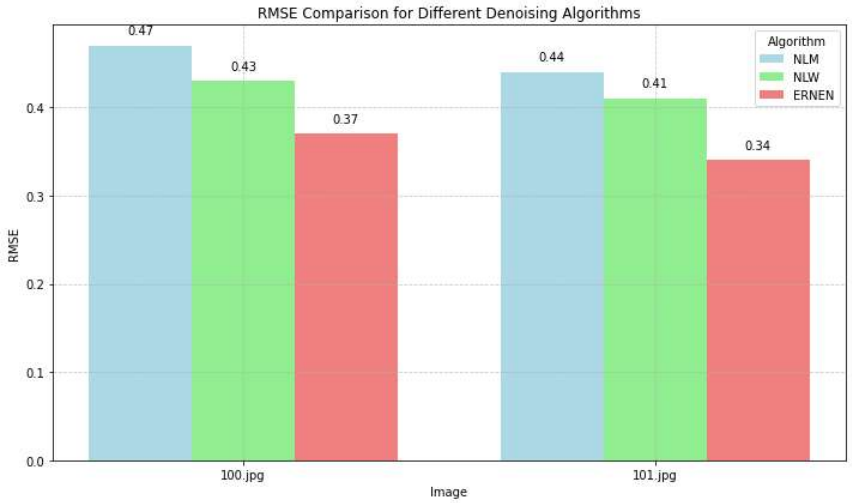

Figure 15: RMSE value comparison chart

The figure 15 shows RMSE value comparisons chart the x axis shows image and the y axis shows RMSE values.

Table 3: Classification performance metrics comparison table

Methods	**Accuracy**	**Precision**	**Recall**	**F-measure**
ResNet 50	93.89	93.65	93.25	93.12
VGG 16	94.01	94.32	94.01	94.21
VGG 19	94.12	94.81	94.27	94.36
Improved VGG 19	95.32	95.24	95.12	95.32

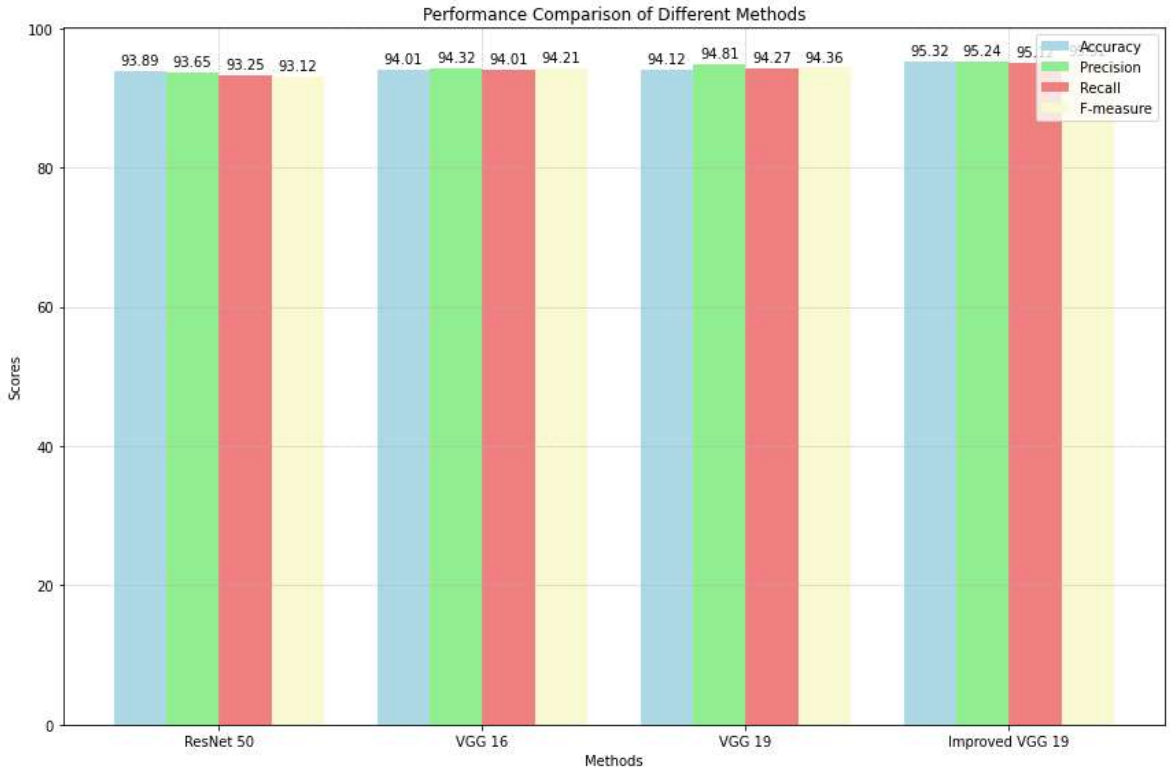

Figure 16: Classification performance metrics comparison chart

The table 3 and figure 16 shows performance evaluation of different models reveals that the Improved VGG 19 outperforms the other methods across all metrics. Specifically, it achieves the highest Accuracy at 95.32%, Precision at 95.24%, and Recall at 95.12% and F-measure at 95.32%. This indicates that the Improved VGG 19 model is superior in correctly classifying instances and minimizing errors. VGG 19 follows closely, with Accuracy of 94.12%, Precision of 94.81%, Recall of 94.27%, and F-measure of 94.36%, demonstrating strong performance but slightly lower than the Improved VGG 19. VGG 16 shows a good performance with Accuracy of 94.01%, Precision of 94.32%, Recall of 94.01%, and F-measure of 94.21%, while ResNet 50, although still effective, lags behind with Accuracy of 93.89%, Precision of 93.65%, Recall of 93.25%, and F-measure of 93.12%. Overall, the data highlights that the Enhanced VGG 19 model provides the most balanced and effective performance in terms of classification accuracy and reliability.

V. Conclusion

There has been great progress in the early identification and treatment of Parkinson's Disease (PD) to the successful prediction of PD using spiral drawing image categorization. Improved PD prediction accuracy and reliability can be possible with the use of cutting-edge machine learning and image processing methods, as shown in this work. By utilizing the Enhanced Residual Noise Elimination Neural Network for preprocessing, the Improved Mask R-CNN for segmentation, CNN with AlexNet for feature extraction, and IVGG19 Networks for classification, the proposed framework achieves a high level of precision in analyzing spiral drawings. The preprocessing step effectively reduces image noise, improving the quality of the input data. Enhanced segmentation with Improved Mask R-CNN ensures that relevant features

are accurately identified, which is crucial for reliable feature extraction. The use of AlexNet for capturing intricate patterns and IVGG19 Networks for classification further refines the diagnostic process, enabling a robust and automated approach to predicting Parkinson's Disease. Overall, the integration of these sophisticated techniques into a cohesive system not only provides a valuable tool for clinicians but also contributes to the broader goal of improving early diagnosis and intervention for Parkinson's Disease. Future work could explore the application of this framework to larger datasets and real-world clinical scenarios to further validate its effectiveness and adaptability. By advancing the capabilities of automated PD prediction, this study supports the ongoing effort to enhance patient outcomes and advance neurological care.

VI. References

1. Ali, S., Hashmi, A., Hamza, A., Hayat, U., & Younis, H. (2023). Dynamic and static handwriting assessment in Parkinson's disease: a synergistic approach with C-Bi-GRU and VGG19. *Journal of Computing Theories and Applications*, *1*(2), 151-162.
2. Almeida, J. S., Rebouças Filho, P. P., Carneiro, T., Wei, W., Damaševičius, R., Maskeliūnas, R., & de Albuquerque, V. H. C. (2019). Detecting Parkinson's disease with sustained phonation and speech signals using machine learning techniques. *Pattern Recognition Letters*, *125*, 55-62.
3. Alshammri, R., Alharbi, G., Alharbi, E., & Almubark, I. (2023). Machine learning approaches to identify Parkinson's disease using voice signal features. Frontiers in artificial intelligence, 6, 1084001.
4. Boutet, A., Madhavan, R., Elias, G. J., Joel, S. E., Gramer, R., Ranjan, M., ... & Lozano, A. M. (2021). Predicting optimal deep brain stimulation parameters for Parkinson's disease using functional MRI and machine learning. Nature communications, 12(1), 3043.
5. Chakraborty, S., Aich, S., Han, E., Park, J., & Kim, H. C. (2020, February). Parkinson's disease detection from spiral and wave drawings using convolutional neural networks: A multistage classifier approach. In *2020 22nd International Conference on Advanced Communication Technology (ICACT)* (pp. 298-303). IEEE.
6. Chintalapudi, N., Battineni, G., Hossain, M. A., & Amenta, F. (2022). Cascaded deep learning frameworks in contribution to the detection of parkinson's disease. Bioengineering, 9(3), 116.
7. Dadu, A., Satone, V., Kaur, R., Hashemi, S. H., Leonard, H., Iwaki, H., ... & Faghri, F. (2022). Identification and prediction of Parkinson's disease subtypes and progression using machine learning in two cohorts. *npj Parkinson's Disease*, *8*(1), 172.
8. Jain, D., Mishra, A. K., & Das, S. K. (2021). Machine learning based automatic prediction of Parkinson's disease using speech features. In Proceedings of International Conference on Artificial Intelligence and Applications: ICAIA 2020 (pp. 351-362). Springer Singapore.
9. Kaur, S., Aggarwal, H., & Rani, R. (2021). Diagnosis of Parkinson's disease using deep CNN with transfer learning and data augmentation. *Multimedia Tools and Applications*, *80*(7), 10113-10139.

10. Kurmi, A., Biswas, S., Sen, S., Sinitca, A., Kaplun, D., & Sarkar, R. (2022). An ensemble of CNN models for Parkinson's disease detection using DaTscan images. *Diagnostics*, *12*(5), 1173.
11. Lilhore, U. K., Dalal, S., Faujdar, N., Margala, M., Chakrabarti, P., Chakrabarti, T., ... & Velmurugan, H. (2023). Hybrid CNN-LSTM model with efficient hyperparameter tuning for prediction of Parkinson's disease. *Scientific Reports*, *13*(1), 14605.
12. Mary, G., & Suganthi, N. (2022). Detection of Parkinson's Disease with Multiple Feature Extraction Models and Darknet CNN Classification. *Computer Systems Science & Engineering*, *43*(1).
13. Mathkunti, N. M., Ananthanagu, U., & Ebin, P. M. (2024, April). Brain Disease Parkinson's Diagnosis using VGG-16 and VGG-19 with Spiral and Waves drawings as Input. In *2024 IEEE 9th International Conference for Convergence in Technology (I2CT)* (pp. 1-5). IEEE.
14. Nilashi, M., Ibrahim, O., Ahmadi, H., Shahmoradi, L., & Farahmand, M. (2018). A hybrid intelligent system for the prediction of Parkinson's Disease progression using machine learning techniques. *Biocybernetics and Biomedical Engineering*, *38*(1), 1-15.
15. Oh, S. L., Hagiwara, Y., Raghavendra, U., Yuvaraj, R., Arunkumar, N., Murugappan, M., & Acharya, U. R. (2020). A deep learning approach for Parkinson's disease diagnosis from EEG signals. Neural Computing and Applications, 32, 10927-10933.
16. Patra, A. K., Ray, R., Abdullah, A. A., & Dash, S. R. (2019, November). Prediction of Parkinson's disease using Ensemble Machine Learning classification from acoustic analysis. In Journal of physics: conference series (Vol. 1372, No. 1, p. 012041). IOP Publishing.
17. Quan, C., Ren, K., & Luo, Z. (2021). A deep learning based method for Parkinson's disease detection using dynamic features of speech. IEEE Access, 9, 10239-10252.
18. Raundale, P., Thosar, C., & Rane, S. (2021, May). Prediction of Parkinson's disease and severity of the disease using Machine Learning and Deep Learning algorithm. In 2021 2nd International Conference for Emerging Technology (INCET) (pp. 1-5). IEEE.
19. Saeed, F., Al-Sarem, M., Al-Mohaimeed, M., Emara, A., Boulila, W., Alasli, M., & Ghabban, F. (2022). Enhancing Parkinson's disease prediction using machine learning and feature selection methods. *Computers, Materials and Continua*, *71*(3), 5639-5658.
20. Salmanpour, M. R., Shamsaei, M., Hajianfar, G., Soltanian-Zadeh, H., & Rahmim, A. (2022). Longitudinal clustering analysis and prediction of Parkinson's disease progression using radiomics and hybrid machine learning. *Quantitative Imaging in Medicine and Surgery*, *12*(2), 906.
21. Severson, K. A., Chahine, L. M., Smolensky, L. A., Dhuliawala, M., Frasier, M., Ng, K., ... & Hu, J. (2021). Discovery of Parkinson's disease states and disease progression modelling: a longitudinal data study using machine learning. The Lancet Digital Health, 3(9), e555-e564.
22. Shahid, A. H., & Singh, M. P. (2020). A deep learning approach for prediction of Parkinson's disease progression. Biomedical Engineering Letters, 10, 227-239.
23. Siuly, S., Khare, S. K., Kabir, E., Sadiq, M. T., & Wang, H. (2024). An efficient Parkinson's disease detection framework: Leveraging time-frequency representation

and AlexNet convolutional neural network. *Computers in Biology and Medicine*, *174*, 108462.
24. Sivaranjini, S., & Sujatha, C. M. (2020). Deep learning based diagnosis of Parkinson's disease using convolutional neural network. *Multimedia tools and applications*, *79*(21), 15467-15479.
25. Taleb, C., Likforman-Sulem, L., Mokbel, C., & Khachab, M. (2023). Detection of Parkinson's disease from handwriting using deep learning: a comparative study. Evolutionary Intelligence, 1-12.
26. Templeton, J. M., Poellabauer, C., & Schneider, S. (2022). Classification of Parkinson's disease and its stages using machine learning. Scientific reports, 12(1), 14036.
27. Vásquez-Correa, J. C., Arias-Vergara, T., Orozco-Arroyave, J. R., Eskofier, B., Klucken, J., & Nöth, E. (2018). Multimodal assessment of Parkinson's disease: a deep learning approach. IEEE journal of biomedical and health informatics, 23(4), 1618-1630.
28. Wang, W., Lee, J., Harrou, F., & Sun, Y. (2020). Early detection of Parkinson's disease using deep learning and machine learning. *IEEE Access*, *8*, 147635-147646.
29. Wang, W., Lee, J., Harrou, F., & Sun, Y. (2020). Early detection of Parkinson's disease using deep learning and machine learning. IEEE Access, 8, 147635-147646.
30. Rajakumar, S., Sreedhar, P. S. S., Kamatchi, S., & Tamilmani, G. (2023). Gray wolf optimization and image enhancement with NLM Algorithm for multimodal medical fusion imaging system. *Biomedical Signal Processing and Control*, *85*, 104950.
31. Castillo Barnes, D., Martínez Murcia, F. J., Jiménez Mesa, C., Salas González, D., Ramírez Pérez De Inestrosa, J., & Gorriz Sáez, J. M. (2023). Nonlinear Weighting Ensemble Learning Model to Diagnose Parkinson's Disease Using Multimodal Data.