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Novel Transfer Learning Approach for Parkinson Disease Detection Using Spiral Drawings

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ABSTRACT One of those global diseases, with above 10 million sufferers globally, is idiopathic Parkinson's disease(PD). It develops slowly and is a chronic condition that establish over time and is caused by the loss of nerve cells. The gradual damage to these brain cells can often cause symptoms like tremors, speech and writing changes, depression, slow movement (bradykinesia), balancing problem and stiffed muscles that may adversely affect the patient's daily activities. PD hits the central nervous system and this disorder mainly effects the coordination of movements which can be extremely distressing in terms of its side effect. Prompt investigation is an effective method for preserving and enhancing quality of life. Our study focuses on creating a model for the early diagnose of Parkinson's by utilizing spiral images. We proposed a advance and novel transfer learning approach and applied various ML techniques to comparisons. We aim to accurately diagnose Parkinson's disease by introducing a novel transfer learning approach-based features engineering method. The suggested model employs a 2D artificial neural network (ANN) to extract spatial characteristics from the image, which are subsequently input into a logistic regression to create a probabilistic feature set for further analysis. Experimental studies have shown that the proposed Artificial Neural Network with Random forest and Logestic regression (ARL model) is effective in predicting Parkinson's disease with 99% accuracy. Model performance is vindicated by hyper-parameter optimization and k-fold cross-validation. This research is promising in detecting Parkinson's disease early using digital imaging and showing promising results.

INDEX TERMS Parkinson's Disease, Spiral Drawing Images, Parkinson's Diagnosis, Smart Feature Engineering, Transfer Learning, Machine Learning(ML), Deep Learning(DL),

I. INTRODUCTION

PARKINSON'S disease (PD) represents a major challenge for modern medicine and is characterized by a severe neurodegenerative disorder. James Parkinson first described this chronic and debilitating disease in 1817, but it continues to challenge scientists and clinicians. It is predominantly a Central Nervous System(CNS) disorder and it has the greatest motor slacks. However, the impact of it is much beyond physical injury and even cognitive & emotional impairments. PD is also a neurodegenerative state that commonly bothers older adults, leading to slowed movement (bradykinesia) along with other symptoms like resting tremor or muscle stiffness [1]–[3]. Other symptoms of it includes loss of sleep and smell, mood disturbances, drooling, constipation, and uncontrolled limb movements during sleep [4]. Researchers used different techniques like Electroencephalogram (EEG) signal [5], gait [6]–[9], acoustic signal [10]–[12], Magnetic Resonance Imaging (MRI) [13], and handwritten signals [14]–[16] to detect the presence of PD.

The symptoms of PD are categorizes by many abnormalities which includes bradykinesia, resting tremor, rigidity, and postural instability. These disorders are caused by the degeneration of dopaminergic neurons in the substantia nigra pars compacta and invariably reduce the quality of life of affected individuals. Additionally, non-physical symptoms such as cognitive decline, depression, and poor physical functioning also contribute to the distress experienced by patients and individuals.

PD continues to be a health challenge, affecting more than 7 million people worldwide with an increasing incidence [17]. Despite extensive research, humans are unable to come up with a cure for it which highlights the importance of new methods for early diagnosis and treatment. Written analysis and spiral sketching have emerged as a promising, noninvasive method for diagnosing PD in its onset phase and provide insight into the motor changes of the disease [18], [19]. A patient with PD can experience various motor and non-motor symptoms which includes tremor, rigidity, cognitive, and auditory impairments . More importantly,the neurological disorder know as Tremor is one of the main symptoms of PD, and this in the points which brings it into the limelight .

The use of AI, especially advances in convolutional neural networks (CNN), offers a new opportunity to develop predictive models for PD diagnosis and characteristic tremor-based classification [**?**]. A CNN-based baseline of PD patients and healthy controls resulted in a binary classification of PD findings. Our approach uses specific tremor patterns exhibited by PD patients to provide a reliable and objective diagnostic method . Diagnosis and classification of Parkinson's disease [17], [18]. Next, we provide an overview of the ANN architecture used in our study, detailing its design and capabilities. Our methods describe our binary classification methods using ANNs, comprehensive data collection, prioritization, and sample training methods . Finally, we present our experimental results and analyze the effectiveness and impact of ANN-based methods in PD identification [20].

PD is a neurodegenerative disease characterized by some chronic symptoms such as tremor, rigidity, and bradykinesia, and cognitive issues are one type of non-motor symptom impairment and sleep disturbances. Early diagnosis of PD is critical for timely intervention to improve patient survival and quality of life. Across a variety of diagnoses, handwriting and drawing have emerged as promising, noninvasive methods for investigating movement disorders associated with Parkinson's disease. Writing and spiral drawing activities require motor control and coordination, making them indicative of motor dysfunction in PD. The spiral drawing task involves participants drawing a spiral pattern on a tablet or paper. This simple activity may reveal motor changes in early PD. Our work adopts various levels of ML for partial version detection. Before anything, we are going to use the Artificial Neural Networks (ANN) to segment the spiral image into distinct components . After that the retrieved features are used as input for multiple classification models, including logistic regression (LR), k-nearest neighbor (KNN), and support vector machine (SVM). By evaluating various classification algorithms, we aimed to determine the best model for distinguishing PD patients from healthy individuals based on spiral images. The main research contributions and advancements on Parkinson's disease classification by our study with ANN-based feature extraction are as follows:

- Here, we have put forward a innovative and novel transfer feature-extraction pipeline that preprocessed and reshaped image data in a competent style to fabricate features of significance from Parkinson's disease as well as its healthy control constituents. This further guards the input data into models by standardizing the way image processing and normalization occur.
- Logistic regression helps us predict class probabilities. Comparing Logistic Regression with other classifiers: We contrasted the performance of our logistic regression model to that of Random Forests, SVM, KNN, and Naive Bayes. During the comprehensive comparison, we observed about how well different models were in classifying Parkinson's disease.
- We also performed a full visualization and analysis of the feature space using 3D visualizations as well as class distribution which helped us to understand more about the dataset. This prevented biased evaluation of the models and provided a summary of the distribution of features along with information on how it affects classification performance.

II. LITERATURE REVIEW

In [17] a previous hybrid classification system proposed in this article combines DL and ML technology and uses handwritten images to assist in the diagnosis of PD. Combining SqueezeNet as the feature extractor and SVM as the classifier, the model attained an accuracy of 91.26% in distinguishing Parkinson's patients and healthy subjects. More importantly, the study addressed the issue of limited data by combining different types of data from paper and digital sources. While the proposed method yields good results, the authors acknowledge that it is necessary to collect additional data and evaluate larger data to increase its robustness. Overall, this work will take significant time to develop tools for accurate diagnosis of PD through the integration of DL and ML models.

[18] These previous research papers highlighted the urgent need for timely detection of PD through transcriptional prediction using DL. This study evaluated six samples: VGG16, VGG19, ResNet18, ResNet50, ResNet101, and Vit, using the NIATS dataset containing transcripts from Parkinson's patients and healthy individuals. More importantly, the VGG19 model combined with the proposed method achieved an average accuracy of 96.67%. The collection, curated by Adriano de Olivera Andrade and Joao Paulo Folado from Uberendia Federal University, includes drawings of 12 healthy people and 15 Parkinson's patients, along with spiral and wave examples. This comprehensive study not only demonstrates the effectiveness of DL models, but also point-up the importance of early recognition in managing the growth of Parkinson's disease.

TABLE 1. Summary of Proposed Methods and Performance Scores

Ref. Year	Dataset	Proposed Method	Performance Score
[17] 2021	Kaggle	SVM (Support Vector Machine)	91.26
[18] 2024	Kaggle	VGG19 DL model	96.67
[19] 2024	GoogleNet, for analysing the datasets	"Cosine Deep Convolutional Neural Network" (CosineDCNN)	89.98
[20] 2023	Kaggle	Descriptive analysis, directed gradient histograms, and a random forest classifier	86.67
[21] 2024	UCI Machine Learning Repository	ResNet50	96.67
[22] 2023	Kaggle	VGG19-INC	98.45
[23] 2021	UCI Machine Learning Repository	Logistic regression, k-nearest neighbors (KNN), and random forest classifier (RFC)	91.00
[24] 2021	HandPD and Kaggle	Convolutional neural networks (CNN)	85.00
[25] 2021	private source	Static Spiral Test (SST) Dynamic Spiral Test (DST) Circular Motion Test (CMT)	99.00
[26] 2021	Neurology in Cerrahpaşa, Istanbul	ForestPA	95.00

[19] This research focuses on the inceptive detection and diagnosis of Parkinson's disease using Internet of Things (IoT) technology, with the aim of improving the caliber of life of patients affected by home care. For this purpose, Cosine Deep Convolutional Neural Network (CosineDCNN), a hybrid DL classifier, was developed. Here, the Sine Cosine Goose Gap Optimization (SCGA) algorithm is used to optimally map the cell to the base station, where the images are preprocessed, enhanced, and features are extracted for disease detection and severity classification using CosineDCNN. The results show that CosineDCNN has better performance in contrast to other techniques, with an accuracy rate of up to 89.98% and a confident prediction rate. In addition, the SCGA model demonstrates impressive performance by achieving low latency and minimal power consumption. This research shows us the promising potential of IoT-based approaches in enabling prompt detection and precise classification of PD severity which gives us a more reliable and significantly more effective method to enhance patient care and improve its survival outcomes.

[20] This article endorse the urgent need for early diagnosis of PD, a neurodegenerative disease that affects motor control. Without early diagnosis, the disease often goes unnoticed until symptoms appear. Using descriptive analysis, a traditional tool for studying human behavior, this article presents a technique using line graphs and wave graphs. Feature extraction and detection using directed gradient histograms is done using a random forest classifier. The results reveals that the model is accurate with 86.67% accuracy in spiral drawing and 83.30% accuracy in wave drawing. The confusion matrix provides information about true positives, negatives, negatives, and false negatives, in addition to the performance of the system. These findings shows the potential of transcription analysis as a noninvasive and easy-to-use method for the inceptive detection of PD, helping to improve diagnosis and monitoring of patients.

[21] In this previous paper addresses the challenge of diagnosing Parkinson's disease (PD) by focusing on positive symptoms. This study used a DL method specialized in neural networks (CNN) and aimed to classify patients suffering with PD and healthy individuals based on spiral and waveform analysis. This test uses various CNN models applied to spiral and wave data from transfer learning. More importantly, the ResNet50 model hit an precision of 96.67% in classifying the image. The main aim is to explore the use of educational changes to improve performance standards. The database consisted of spiral and wave diagrams drawn using paper, tablets, and pen by 55 participants, including 28 Parkinson's patients and 27 healthy controls. Additional analyzes compared samples from PD and healthy groups to identify differences. Although this work is based on CNN architecture, learning migration gives us a significant potential for advancing the process and increasing the efficiency in future research. Enhancing datasets with different attributes can also improve the partial release of resources.

[22]This research attempts to improve the accuracy of early diagnosis of PD through DL models, and also focuses on enhancing the reliability of predictions. Recognizing the challenge of understanding how classifiers make PD predictions, this study introduces VGG19-INC, a new adaptive model that outperforms other methods with 98.45% accuracy. Leverage descriptive intelligence (EXAI) techniques such as LIME to identify predictive patterns by identifying key features in spiral and wave patterns that aid diagnosis. The data includes spiral and wave pattern diagrams from 102 subjects, divided into training and practical applications. By combining the results of two DL transformations and optimizing the learning, the VGG19-INC model is recommended for good diagnosis, which is verified by comparing and interpreting LIME. These findings aids in the development of more reliable as well as transparent diagnostic criteria for PD, providing insight into future research and clinical use of it.

[23] Parkinson's disease (PD) causes serious problems in diagnosis and care, especially in underdeveloped regions. In this study, digital computers were used for data collection and detailed analysis of static and dynamic spiral drawings drawn by Parkinson's patients. The study achieved approximately 91% accuracy by extracting aerial and kinematic variables from a sample of 25 Parkinson's patients and 15 healthy controls, using vehicle acquisition engineering and four ML classifiers (logistic regression). The nearest. (KNN) classifier and random forest classifier (RFC). This file contains a sample drawing from the UCI Machine Learning Repository provided by Istanbul University. Three types of spiral stretch tests (static spiral test (SST), dynamic spiral test (DST), and

stability test) are performed to evaluate negative symptoms. The key features and their associated values to obtained from these tests contribute to classification accuracy.

[24] This study uses convolutional neural networks (CNN) to help inceptive detection of PD using hand movements. This study evaluates various CNN architectures and targets using data from HandPD and Kaggle. Although the spiral map achieves 85% accuracy, problems remain, including small data and conflicting problems. This work suggests future directions such as collecting larger datasets, addressing data gaps, and investigating deeper learning methods such as k-fold cross-validation for model development. Overall, this research emphasizes the importance of good data and appropriate sample selection to increase the precision of diagnosis of Parkinson's disease.

[25] These previous studies have highlighted the potential of spiral plots as excellent predictors that can be used to differentiate patients with PD from controls with successfully progressing area under the curve (AUC0.99). While recognizing the need for further refinement of functional maps and study designs to ensure accurate diagnosis, this study demonstrates the promise of this approach in supporting the assessment of PD. Due to the increasing incidence of Parkinson's disease and the worldwide shortage of neurologists, it is important to develop and implement affordable, prescription-based diagnostic tools for Parkinson's disease. This technology could reduce the global burden of the disease by enabling community health workers and primary care providers to identify the same people at risk of Parkinson's disease.

[26] The article presents an innovative approach to Parkinson's disease (PD) diagnosis using decision forests, specifically exploring SysFor, ForestPA, and Random Forest algorithms. By dynamically adjusting the number of decision trees and training instances, the study aims to optimize detection accuracy. ForestPA emerges as the most promising detector, achieving a remarkable accuracy of 94.12% to 95.00% with minimal decision trees. Notably, ForestPA demonstrates superior performance with just nine decision trees for the Istanbul dataset and one for the Spanish dataset. While Random Forest yields a slightly higher average detection accuracy of 93.58%.

III. METHODOLOGY

The intended research model aspires to predict PD using the effective model as shown in Figure 1. Using the Kaggle dataset, we applied the quality architecture (ARL)-based transfer learning algorithm to derive the best features from graph data to improve PD progression. The results of the transmission are divided into two groups, maintaining the ratio of 80/20. The larger part (80) is devoted to training the model, while the remaining 20 is devoted to working on ML. The improved method, which showed the best performance, was then applied to improved function of PD from the Kaggle dataset consisting of spiral drawings.

A. SPIRAL DRAWING IMAGES

The spiral pattern dataset [27], publicly available from the well-known Kaggle repository, is used to conduct the research experiments. The image dataset is consists of 102 files which belongs to two classes, where the first one is "healthy" and the other one is "parkinson's". Since the dataset is too small, we applied the augmentation technique [28] to create more images for better performance. After augmentation the dataset reaches to 695 files for two classes, "healthy" and "Parkinson's", as shown in Figure 2. The separation explains that the Parkinson class (1) is consists of 360 image samples and the other class know as the normal class (0) is consist of only 335 samples. The sample of the images, with target labels, of both classes used in the research are shown is shown in Figure 3.

B. AUGMENTATION TECHNIQUES AND DATASET EXPANSION

For our research, we utilized different data augmentation techniques to enhance the dataset and to elevate the diversity and robustness of the model. Starting with a dataset of 102 original spiral images, we applied the following augmentation methods:

- Rotation: The images were rotated randomly within a range of ±17.25 degrees to simulate various drawing angles and orientations.
- Zoom: Both zoom-in and zoom-out transformations were applied to introduce scale variability, mimicking different levels of detail in the spirals.
- Horizontal Flip: Images were flipped horizontally to create mirrored versions, enhancing spatial invariance in the dataset.

Through these augmentation techniques, the dataset was expanded to 695 images, significantly increasing its size while preserving the underlying patterns crucial for the classification of healthy versus Parkinson's spirals. Some examples of augmented images are shown in TABLE 2.

C. NOVEL TRANSFER LEARNING-BASED FEATURE ENGINEERING

In the following research , we have come up with a new and exciting approach using transfer learning to help diagnose Parkinson's disease , all by analyzing human spiral pattern images, which is fresh and innovative way to use data for something that really matters. You can see how our proposed feature engineering method works in Figure 4. It's all laid out there! Our proposed ARL method brings together two powerful techniques to transfer learning experience and create a brand-new and unique feature set. We start with extracting spatial features from the spiral pattern image dataset using Artificial neural networks(ANN). These features are then fed into the Logestic Regression method to take it to the next level. From these spatial features, a set of probabilistic features based on transfer learning is formed. A set of probabilistic features is used to build an application

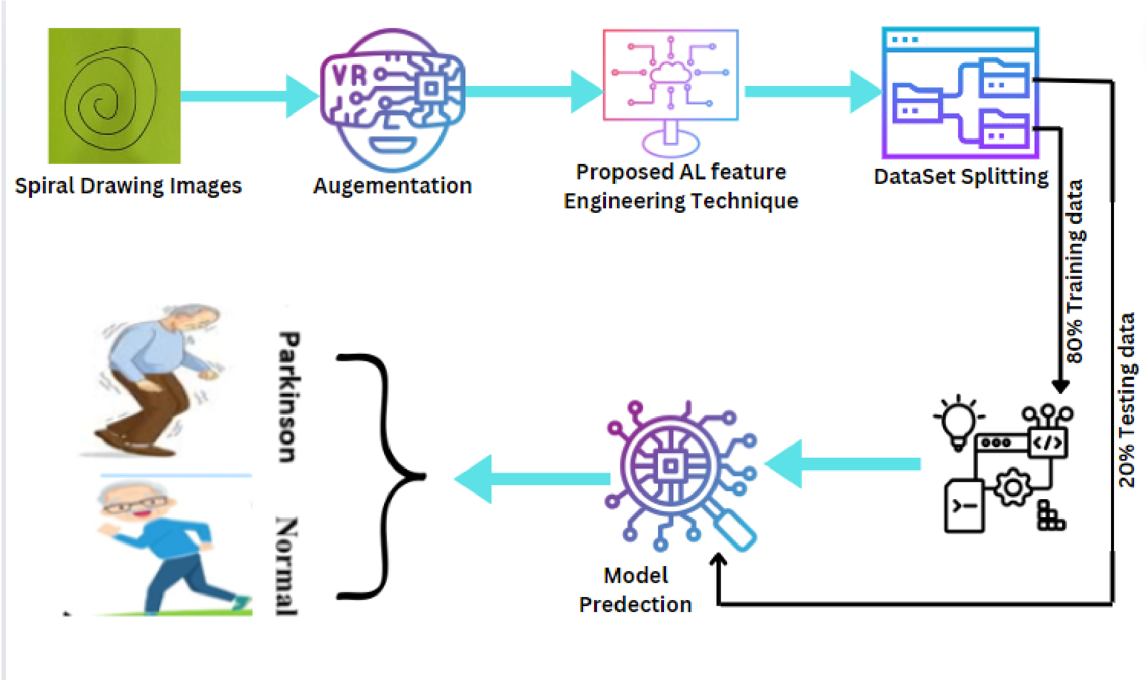
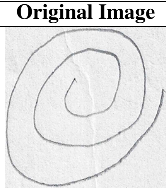
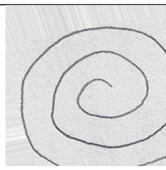
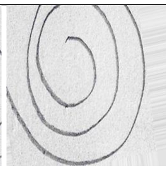
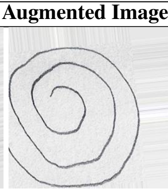
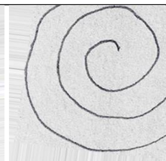
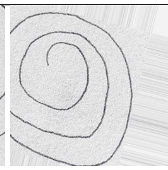
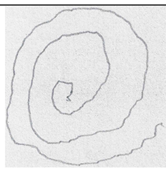
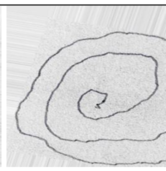
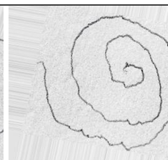
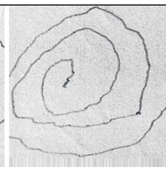


FIGURE 1. Proposed Methodology for Parkinson's Disease Detection

TABLE 2. Examples of Original and Augmented Spiral Images

Type	Original Image	Augmented Images				
Healthy Spiral						
Parkinson Spiral						

detection method for Parkinson's disease using human spiral pattern image data. The newly proposed feature based on transfer learning revolutionizes the prediction of PD from high-performance spiral pattern images.

1) SPATIAL-FEATURES

Imagine that the input data set D consists of N samples, in which each sample is a 2D image represented by a matrix $\mathbf{X}$ â R$^{H\tilde{A}W}$, where H and W represent the height and width of the image, respectively. The goal of this study is to retrieve spatial features using a 2D ANN model. In an Artificial Neural Network (ANN), layers are typically made up of neurons that perform linear transformations followed by nonlinear activation functions to capture complex patterns in the input data [29]. Let $\mathbf{X}_l$ denote the output of the neurons at the l-th layer of the ANN. We can express the operation on the layer l as:

$$\mathbf{X}_l = \sigma(\mathbf{W}_l \mathbf{X}_{l-1} + \mathbf{b}_l),$$

where $\mathbf{W}_l$ represents the weight matrix connecting layer $l-1$ to layer l, $\mathbf{X}_{l-1}$ is the output from the previous layer, $\mathbf{b}_l$ is the bias term, and $\sigma(\cdot)$ is the activation function, such as the ReLU or sigmoid function.

In an ANN, the process starts with the input layer, where each and every neuron represents a feature of the input data. The input layer is followed by one or multiple hidden layers, which are composed of neurons that apply weights and biases to the input and then pass the result through a non-linear activation function. These hidden layers capture complex patterns and interactions in the data. The ANN ends by making prediction at the final layer, which is the output layer network. This prediction is based on the data, which transformed at every layer from start to end.

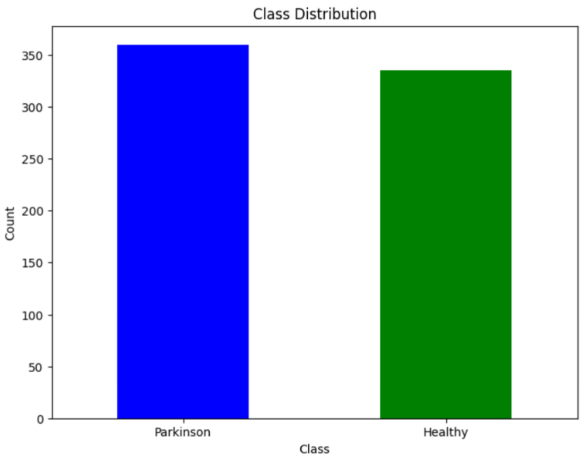


FIGURE 2. Sample images used in the research, with target labels

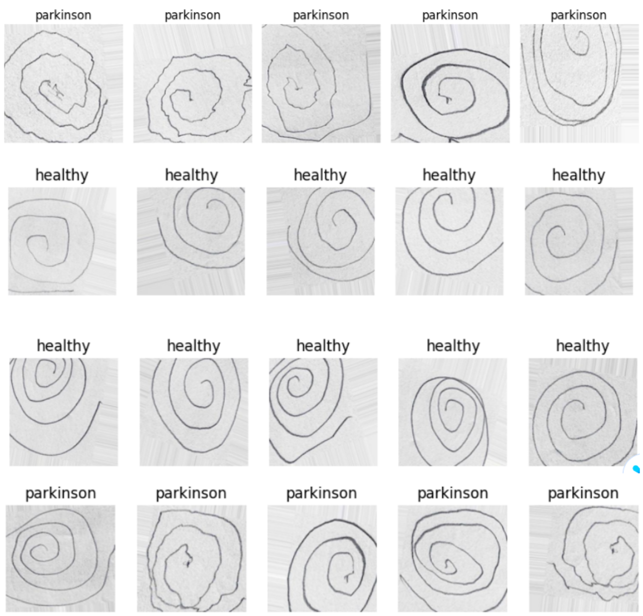


FIGURE 3. Spiral drawing images data analysis with target labeled

After applying multiple layers, we ended up having a set of neuron activations $\{\mathbf{X}_l\}_{l=1}^{L}$, where L denotes the total number of layers in the ANN model. Each layer breaks down the data in a new way, picking up on more and more complex patterns as you go deeper.

D. IMAGE DATA SPLITTING

Data splitting is a must is supervised ML approach. In Splitting the dataset is basically used to split into two subsets: training and testing. The ratio taken for the division of data in this experiment has been 80:20. 80% of all the images are used for machine training purpose and rest of the 20% are used for machine testing purpose.

Therefore, the models' parameters are adjusted on the training set, and the test set is allowed to test the model's performance on unseen-data. Splitting the dataset avoids over-fitting, that is usually encountered when the models(algorithms) is trained using insufficient data. Splitting your dataset is the key to developing powerful and robust ML models.

E. MACHINE-LEARNING DEEP-LEARNING METHODS

The advent of machine-learning and deep-learning techniques has lead to unprecedented successes on image classification tasks [30], [31]. In ML Logistic Regression (LR), XGBoost (XGB), and Support Vector Machine (SVM) are commonly used models for classification problems. Among DL approaches, CNN is widely used in image detection and shows high performance. CNN captures the spatial properties of image data through multiple layers of filters and understand complex representations of the data [32]. Image classification can be better tackled with high performance by training the ML methods on the top of features extracted from CNN [33].

After evaluating simple ML techniques, we applied an Artificial Neural Network (ANN) for feature extraction and classification of spiral drawings. The extracted features were used to build various machine-learning methods, including random forest classifier, support vector machines, Naïve-Bayes classifiers, Xgboost, and k-neighbors.We took a look at the layered setup of the ANN model used for feature extraction in the Table 4.

TABLE 3. Summary of the ANN model architecture

Layer (type)	Output Shape	Param #
input_layer (InputLayer)	(None, 49152)	0
dense_1 (Dense)	(None, 128)	6291584
dense_2 (Dense)	(None, 600)	77400
Total params		**6368984** (24.30 MB)
Trainable params		**6368984** (24.30 MB)
Non-trainable params		**0** (0.00 Byte)

F. HYPERPARAMETER TUNING

Hyper-parameter tuning is an important part in ML in which optimal set of hyper-parameters are selected for a specific predictive model. In hyper-parameters tuning we used different values for hyper-parameters, and evaluate the model's performance against test dataset. The goal of hyper-parameters tuning is to find the set of hyper-parameters that yields the best performance on the test dataset. Hyper-parameters tuning is important because it can profoundly improve the performance of the applied ML method. The Hyper-parameters optimization of the used models is examined in the following Table 4.

IV. RESULTS DISCUSSIONS

In this section, we analyze the performance test results and discuss the AI-based application methods. The experimental setup and results are explained by comparing them with spiral pattern image data. Performance metrics such as precision, recall, f1 score, and accuracy are used to evaluate the model

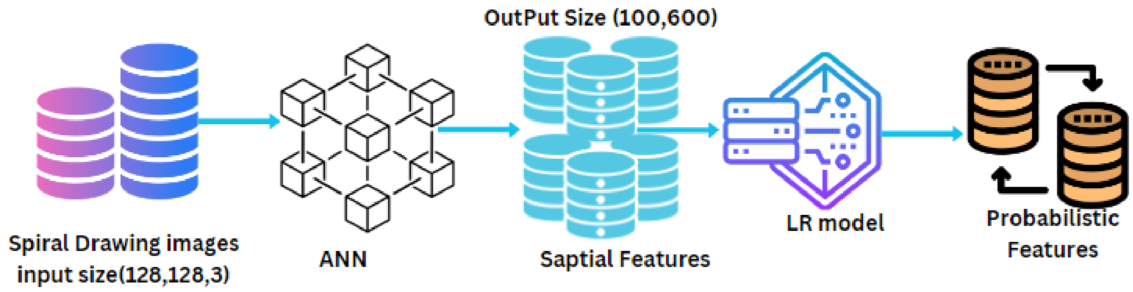


FIGURE 4. The proposed workflow based on novel feature engineering using transfer learning approach.

TABLE 4. Summary of the model hyperparameters

Technique	Hyperparameter values
ANN	activation function: "softmax", optimizer: "adam", loss: "cce"
RF	max_depth: 20, random_state: 0, n_estimators: 10
LR	max_depth: 20, random_state: 0, n_estimators: 10
KNN	max_depth: 10, random_state: 0, n_estimators: 10
SVM	max_depth: 10, random_state: 1, n_estimators: 10

performance.To sum it all up, the results and discussion part is imperative for really digging into how the proposed ML and DL techniques can help us tackle the real-world problems. In this study, we evaluate DL model CNN and other various Simple ML models to classify images of parkinson's disease compared to healthy-images. Evaluation methods include K-Nearest Neighbor (KNN), Logistic Regression (LR), XGBoost, Naive Bayes, Support Vector Machine (SVM), and Random Forest (RF). Each model is checked based on its accuracy. The accuracy of the RF model is 0.5533, and the accuracy of the KNN model is 0.5067. The LR model has an accuracy of 0.5267, while the XGBoost performs well with an accuracy of 0.58. The accuracy of the Naive Bayes model is 0.4933, and the SVM model shows the performance of the LR model with an accuracy of 0.5267. All ML models showed average accuracy, which is maximum 55%, by RF. The summery of hyper parameters of all ML models can be seen in the Table 3 In this study, our proposed method, ARL achieved the highest accuracy among the employed ML models. The ARL method demonstrated a superior performance with an accuracy of **98.56%**, showcasing its effectiveness in leveraging spatial features extracted from spiral pattern images.

A. *EXPERIMENTAL SETUP*

We employed the use of some widely available Python packages and libraries such as sklearn, keras, and tensorflow to develop the ML models. All of the research experiments are run in the Google Colab, accessed through a high-performance GPU-backend with 12GB RAM and 90GB of disk space, even though a system using an Intel(R) Core(TM) processor was used to conduct experiments in this work. The experiments carried out involved training and testing the model's performance using the Python 3 programming language. The metrics used in the experimentation include accuracy, precision, recall, f1 score, and time complexity while evaluating ML model performances.

B. *CONVOLUTIONAL-NEURAL NETWORK RESULTS*

Use classic CNN to process Parkinson's disease images and evaluate performance for better comparison. A time-series based-analysis was perform while feeding the CNN application for 10 epochs, as shown in Figure 5.After analyzing this,it looks like the neural network picked up on a lot of patterns from each stage of Parkinson's disease, mapping the data and adjusting the weights in the network as it learned. The analysis of Figure 6 shows that the training accuracy and validation scores also increase with training time. The highest training accuracy score after 10 epochs is 64, and the validation score is above 65. The research summarize that while classic artificial neural networks perform well during training, they are not the best. The comparative performance of the data is shown in Figure 12. The metric scores for accuracy, precision, and F1 are 51.33, 54.17, and 26.26, respectively. The analysis concluded that the use of artificial neural networks scored poorly in diagnosing Parkinson's disease using images.

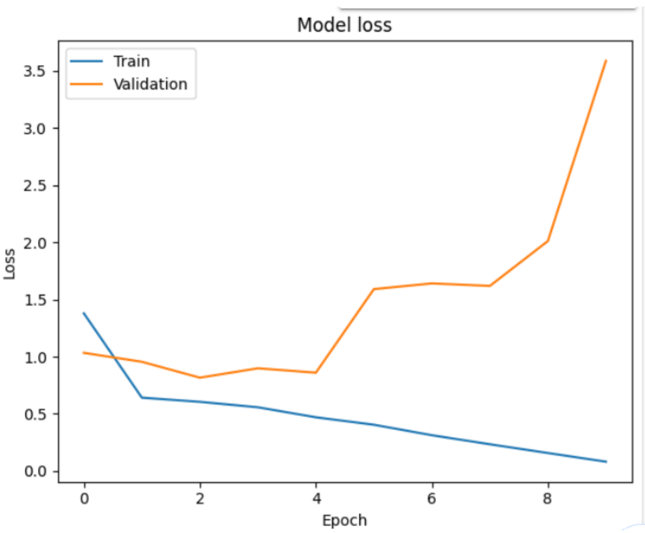


FIGURE 5. The time series-based performance scores analysis of applied Convolutional neural network during training.

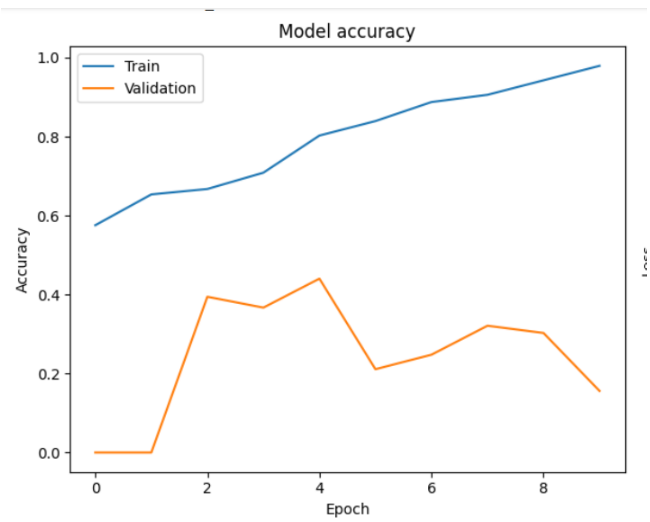


FIGURE 6. The time series-based performance scores analysis of applied Convolutional neural network during training.

C. RESULTS WITH SIMPLE ML TECHNIQUES

In the first experiment, we employed a range of classical ML techniques to classify images of Parkinson's disease versus healthy subjects.The evaluated models included K-Nearest Neighbors (KNN), Logistic Regression (LR), XG-Boost, Naive Bayes, Support Vector Machine (SVM), and Random Forest (RF), with accuracy as the main evaluation metric. The models showed different levels of efficiency. XGBoost achieved the highest accuracy of 58, while Naive Bayes achieved the lowest accuracy with an accuracy of 49.33. The Random Forest model achieved an accuracy of 55.33, and KNN achieved an accuracy of 50.67. Both the LR and SVM models showed an accuracy of 52.67. Overall, the

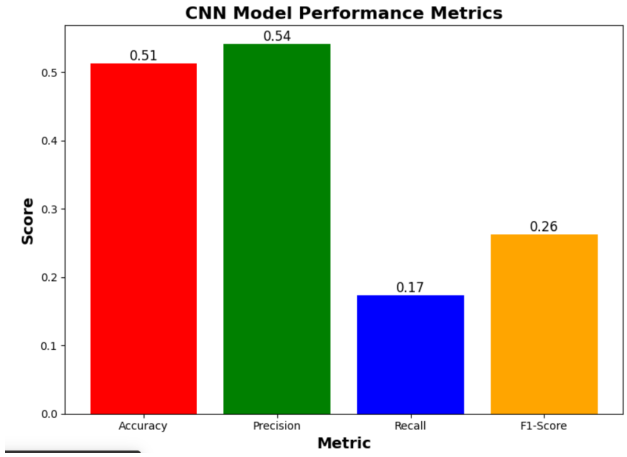


FIGURE 7. The bar chart provides an analysis of the performance metrics for the convolutional neural networks applied to unseen test data.

performance of these classical ML models was suboptimal, indicating the necessity for more advanced techniques or additional feature extraction to improve classification accuracy in distinguishing based on the image data, we compare Parkinson's disease patients with healthy subjects. The performance of the different ML methods is compared in detail. You can find this comparison in Table 4. The comparative

TABLE 5. Model Performance Metrics By using the Simple ML Techniques

Model	Accuracy (%)	Precision	Recall	F1-score
LR	52.67	0.5385	0.3733	0.4409
SVM	52.67	0.5385	0.3733	0.4409
KNN	50.67	0.5094	0.36	0.4219
RF	55.33	0.5571	0.52	0.5379
NB	49.33	0.4964	0.92	0.6449
XGBoost	58.00	0.5833	0.56	0.5714

performance analysis based on bar graphs of the ML methods used with spatial features is depicted in Figure 8. Upon visual inspection, it is evident that the ML models exhibited varying degrees of performance across the assessed methods. The

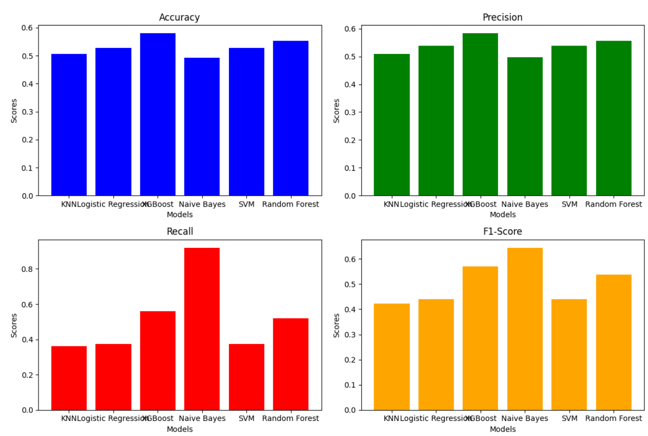


FIGURE 8. The bar chart on the performance of ML models

confusion matrix, depicted in Figure 9, gives a comprehensive overview of the performance of ML techniques with spatial features in our study. This matrix is the representation of summary of the predictions made by the model as compare to the actual ground truth labels of the dataset. By analyzing the confusion matrix, we can get valuable insights including accuracy, precision, recall, and F1-score. We can also dive into the strengths and vulnerabilities of each model, thereby identifying potential areas for improvement in our PD detection task.

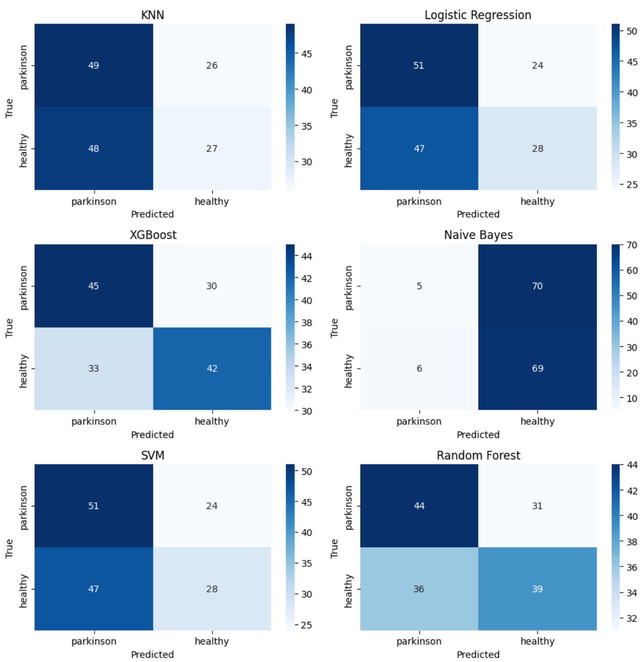


FIGURE 9. The bar chart on the performance of ml models

D. *RESULTS WITH SPATIAL FEATURES*

We use DL-based artificial neural networks (ANN) to retrieve spatial features from spiral pattern image data and assess the performance outcomes. Additionally, we experiment with advanced ML methods using these extracted features. A comparison of the performance of these techniques by utilizing the spatial features is provided in Table 5. The study shows

TABLE 6. Model Performance Metrics With Spatial Features

Model	Accuracy (%)	Precision	Recall	F1-score
LR	98.56	0.98	0.98	0.98
SVM	97.84	0.97	0.98	0.98
KNN	96.40	0.97	0.95	0.96
RF	96.40	0.97	0.95	0.96
NB	54.68	0.51	0.74	0.60
XGBoost	50.36	0.48	0.48	0.48

that the applied Naive-bayes and Xgboost models achieved low accuracy scores of 54.68 and 50.36. The Precision scores obtained by Naive-bayes and Xgboost methods are 0.51 and 0.48, which are the lowest in comparison with other models. The applied model of KNN achieved the accuracy score of 96.40, which is much better than Naive-bayes and Xgboost methods. The KNN method achieved an accuracy of 0.97. The RF method achieved an accuracy of 96.40 points and 0.97 points. The SVM method achieved an accuracy of 97.84 points and an accuracy of 0.97 points. The SVM and RF models have higher accuracy, but log regression is slightly better than the two methods. The LR method achieved an accuracy of 98.56 points and an accuracy of 0.98 points. From the analysis results, we conclude that the LR method achieved a good accuracy of 98.56 points by using the extracted spatial features. A comparative analysis of the performance of the employed ML methods with spatial features based on bar charts is shown in Figure 7. Visual inspection shows that the ML methods perform poorly with spatial features extracted from the spiral pattern images. The LR method achieves the maximum accuracy of 98.56. A comparative analysis of the performance of the employed ML methods with spatial features based on bar charts is shown in Figure 5. Visual inspection shows that the ML methods achieve low performance scores for two methods (Xgboost and Naí¡ve Bayes). Using spatial features extracted from the original spiral pattern images, the other methods (RF, LR, SVM, KNN) obtained higher performance metrics. In this analysis, the LR method achieved an accuracy of up to 98.56, which is the best approach.

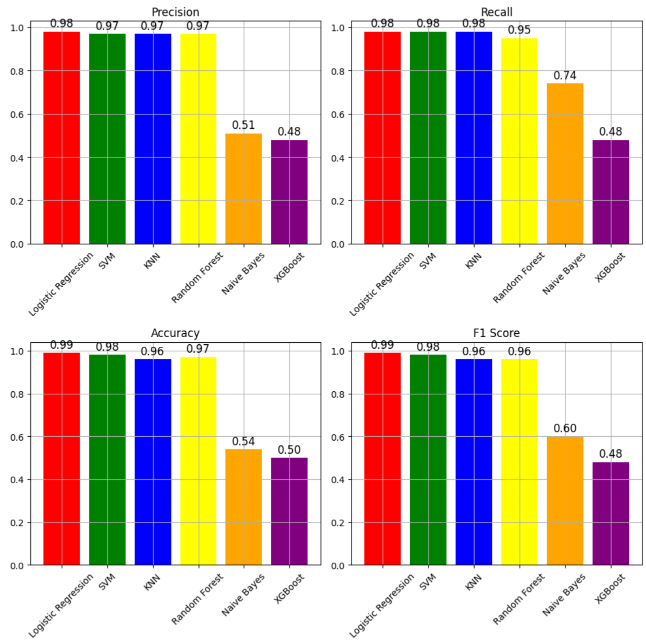


FIGURE 10. The bar chart on the performance of ml models

A comparison of the performance of ML methods using spatial features is presented in Figure 8. Upon visual inspection, it is evident that two methods, XGBoost and Naïve Bayes, performed less effectively, while the remaining methods showed better results. These methods, which utilized spatial features extracted from the original spiral pattern images, include Random Forest (RF), Logistic Regression

(LR), Support Vector Machine (SVM), and K-Nearest Neighbors (KNN). Among them, Logistic Regression (LR) stood out with the highest accuracy, achieving 98.56. Figure 7 displays the analysis matrix of the ML methods incorporating spatial features. The confusion matrix, which summarizes the model's predictions against the true labels, is a valuable tool for evaluating the model's performance. By examining its metrics, one can gain a deeper understanding of the model's strengths and weaknesses and identify areas for future improvement.

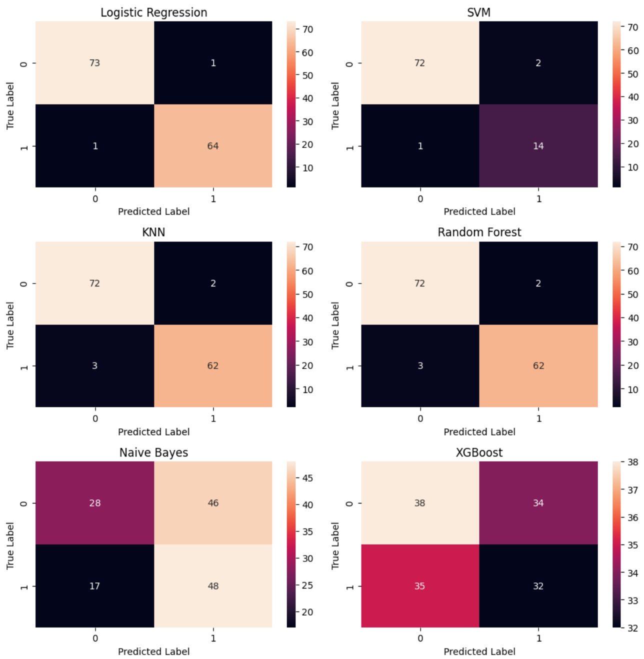


FIGURE 11. The confusion matrix analysis of ML techniques

E. KFOLD CROSS VALIDATION BASED PERFORMANCE ANALYSIS

Table 5 displays the results of k-fold cross-validation analysis employed to evaluate prediction performance for all models. A ten-fold validation for each techniques is used to evaluate both feature datasets. The results show that extracted spatial features do not perform well any more even when cross-validation was applied. Logistic Regression (LR) model, which also achieved the highest k-fold accuracy of 0.93 The study results prove that all the proposed methods are verified and generalizable in predicting Parkinsons disease based on spiral drawing images. Figure 8 — Barplot of the performance for most frequent words feature across two different sets, using all methods with10-fold validation

F. ANALYSIS OF RUNTIME COMPUTATIONAL COMPLEXITY

The Table 6 provide the comparative analysis of runtime computation of applied ML methods during training. The computational complexity allows us to estimate that the implemented compared ML methods use much runtime computational cost with spatial feature data. The highest times are RF and LR with 0.17 seconds and 0.18 milliseconds, respectively The used machine-learning model canbe trained in a lesser time as compared to other approaches which are using spatial features.

TABLE 7. Cross-Validation Accuracy of Different Techniques

Techniques	k-fold Accuracy	Standard deviation (±)
RF	0.89	0.07
LR	0.93	0.06
SVM	0.91	0.05
KNN	0.68	0.03
Naïve bayes	0.84	0.06
Xgboost	0.86	0.04

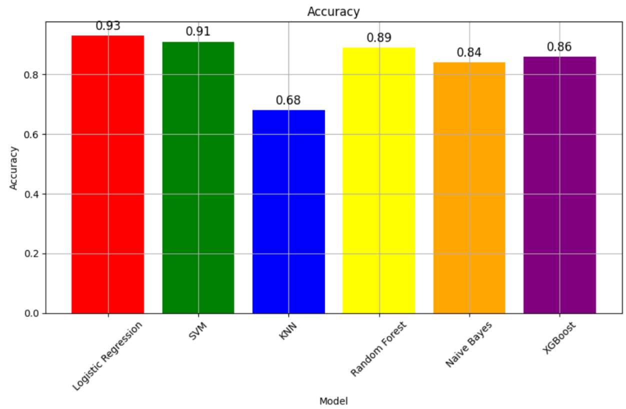


FIGURE 12. The K-fold analysis of ML techniques

TABLE 8. Runtime Computational Cost of Different Methods

Methods	Runtime Computational Cost (Seconds)
LR	0.18
SVM	0.19
KNN	0.24
RF	0.17
Naïve Bayes	0.13
XGBoost	4.36

G. COMPARISON OF SIMPLE ML METHODS AND SPATIAL FEATURES

The incorporation of feature extraction techniques was pivotal in achieving superior performance compared to simple ML models. By leveraging feature extraction methods, we harnessed the intrinsic characteristics of the data, enabling the models to identify subtle patterns and intricate spatial relationships within the images. This empowered the models to come up with more informed and precise predictions, ultimately leading to significantly improved classification accuracy.

Feature extraction techniques played a crucial role in enhancing the discriminatory power of the models by transforming raw image data into meaningful representations that encapsulate relevant information pertinent to the task at hand.

Through this process, we effectively reduced the dimensionality of the data while preserving its discriminative capacity, thus enabling the models to focus on the most salient features essential for classification.

Moreover, the utilization of feature extraction techniques enabled us to capture and encode spatial information inherent in the images, thereby enriching the input data with valuable contextual insights. This holistic approach facilitated a more comprehensive understanding of the fundamental patterns and structures present in the images, consequently empowering the models to make more accurate and reliable predictions.

In essence, the integration of feature extraction techniques elevated the performance of our models to unprecedented levels, surpassing the capabilities of traditional ML approaches. By leveraging these advanced methodologies, we not only achieved remarkable accuracy but also unlocked the full potential of our models in tasks such as Parkinson's disease detection.

H. DISCUSSION

Two dimension Spiral drawing images of the people hands to diagnose Parkinson using advanced neural network-based feature engineering techniques. Each applied model is evaluated by a wide range of results experiments. We mainly use the output of spiral drawing images, to extract spatial and probabilistic aspects that are helpful to assess deployed machine-learning techniques. From the Global Results overview, we see that ML applied to features extracted from spiral images provided high performance benefits as well.

Moreover, we demonstrated the improvements related to performance enhancement of applied ML algorithms by exploiting feature space analysis in relation to the proposed CL technique.Our results endorse that the LR model performs better in the proposed range.. Additionally, we have evaluated the computational cost of used machine-learning methods to measure prediction delays in symptomatic Parkinson. In summary, our proposed work could change the game of Parkinson

V. CONCLUSION

This study highlights the potential of artificial intelligence, specifically Artifical Neural Networks (ANNs), in developing predictive models for diagnosing PD. Our research involves using a variety of ML techniques to classify and analyze data on connections between people with Parkinson's and healthy individuals. The AL-based approach demonstrated the ability to extract significant spatial features from the drawing data, which were then used to train different classification models. Among the evaluated models, the Logistic Regression (LR) technique achieved the best performance with an accuracy score of 98.56% and a precision score of 0.98. This high level of accuracy and precision underscores the effectiveness of the LR technique in classifying PD using the extracted spatial features from spiral drawing images. The bar chart-based comparative performance analysis illustrated in Figure 7 confirms the superior performance of the LR technique.

Our findings underscore the potential of combining handwriting and drawing analysis with advanced ML techniques for early and accurate PD diagnosis.In future, researchers should focus on enhancing the model's accuracy, exploring additional features, and validating the approach on larger datasets to establish a robust diagnostic tool that can greatly enhance patient outcomes and overall quality of life.

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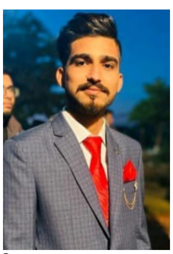
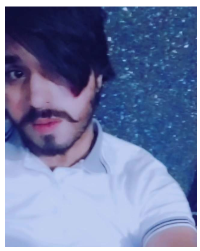


MUHAMMAD RIZWAN a student at KFUEIT, I am delighted to present our research findings. This study represents our dedication to exploring new avenues in our field of study. With meticulous research and analysis, we aim to contribute valuable insights to the academic community. I extend my gratitude to my co-authors and mentors for their guidance and support throughout this endeavor. Together, we strive to make a meaningful impact through our work.

MUHAMMAD SHADAB ALAM HASHMI a respected senior lecturer and PhD scholar at KFUEIT, brings invaluable expertise to this research project as the second author. His extensive knowledge and academic prowess have been instrumental in shaping our study's direction and methodology. With his guidance, we have navigated through complexities and achieved significant milestones in our research journey. Dr. Hashmi's dedication and mentorship have been instrumental in ensuring the quality and rigor of our work. We are grateful for his unwavering support and invaluable contributions to this endeavor.

SYED MUQTASEED ALI a diligent student pursuing a Bachelor's in Computer Science at KFUEIT, serves as the third author, playing a pivotal role in our research endeavor. His keen eye for detail and analytical skills have been instrumental in meticulously reviewing the work of other authors, ensuring its accuracy and coherence. Despite being in the early stages of his academic journey, Muqtaseed has demonstrated exceptional commitment and dedication to the project. His insightful feedback and thoughtful contributions have significantly enriched the quality of our research output. We extend our gratitude to Muqtaseed for his invaluable support and collaboration throughout this process.



KAMRAN ALI a diligent student pursuing a Bachelor's in Computer Science at KFUEIT, is recognized as the fourth author of our research. Kamran played a crucial role in our project by assisting in the review of contributions made by other authors. His keen eye for detail and analytical skills have been instrumental in ensuring the coherence and accuracy of our work. Kamran's dedication and commitment to the review process have significantly contributed to the refinement and enhancement of our research findings. We extend our sincere appreciation to Kamran for his invaluable contributions to our project.

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