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Drawing Classification for Early Detection of Parkinson's Disease: CNN and Transfer Learning Models

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Abstract: *In this study, a new Convolutional Neural Network (CNN) architecture is developed to classify the drawings of individuals with Parkinson's disease and healthy individuals in Wave and Spiral classes. The dataset used is the Parkinson's Drawing Dataset, which contains drawings related to Parkinson's disease. The designed Proposed CNN model is compared with five different transfer learning models in classifying drawings of Parkinson's disease and healthy individuals: VGG16, DenseNet169, MobileNetV2, ResNet50, and EfficientNetB7. The results show that the Proposed CNN outperforms all other models in accuracy, precision, recall, and F1 score metrics for both classes (Wave and Spiral). The Proposed CNN achieves 96.15% accuracy in the Wave class and 95.10% accuracy in the Spiral class, with particularly high performance in metrics such as precision (97.96%) and F1-score (96.02%). These findings show that the Proposed CNN model is a powerful tool for early diagnosis of Parkinson's disease and accurate classification of healthy individuals. In conclusion, the novel CNN architecture has significant potential in the diagnosis of Parkinson's disease by providing better results compared to transfer learning methods. This study emphasizes that drawing-based classification methods can be an effective tool in the diagnosis of Parkinson's disease and can be used in clinical applications.*

Keywords: *Parkinson's Disease Diagnosis, Convolutional Neural Network, Spiral and Wave Drawings*.

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I. INTRODUCTION

Parkinson's disease (PD) is a neurological disorder that develops as a result of the loss of dopamine-producing brain cells, leading to significant impairments in motor functions. It manifests itself with symptoms such as tremor, muscle stiffness, slowing of movements and balance disorders [1]. Early diagnosis of PD and monitoring the progression of the disease is of great importance in the treatment process.

The integration of artificial intelligence (AI) and deep learning (DL) technologies is playing an increasingly important role in the diagnosis and treatment of Parkinson's disease. While AI aims to improve the human-like thinking, learning and problem-solving abilities of computers in general, deep learning, as a subfield of AI, is a powerful tool for learning from large datasets and recognizing complex patterns [2]. Deep learning has the ability to classify and predict with high accuracy, especially by working with large datasets, and this ability is very useful in early diagnosis and monitoring of Parkinson's disease [3]. In tests that assess motor skills, such as the Parkinson's Drawing Test, deep learning algorithms can more precisely determine the stage and severity of the disease by analyzing patients' drawings. In this context, deep learning technologies reinforce the power of artificial intelligence in the clinical evaluation of Parkinson's disease, offering a more objective and efficient monitoring process.

In the diagnosis of Parkinson's disease, the images obtained from the Parkinson Drawing Test constitute an important source for the development of deep learning-based classification systems. In this context, a dataset is used to analyze the motor skills of healthy individuals and Parkinson's patients on simple drawing shapes such as spirals and waves. The dataset contains images of drawings from both groups (healthy and Parkinson's patients) for use in the diagnosis and stage classification of Parkinson's disease. These images are further divided into training and test groups in order to be able to compare or reproduce the results from the original publication. . Deep learning algorithms, in particular convolutional neural networks (CNN), can be trained to perform classification on these drawings. The training group is used to learn the model, while the testing group is used to evaluate the accuracy of the model. Since drawings of Parkinson's patients are considered as indicators of motor disorders, deep learning algorithms can work with high accuracy to classify the presence, stage, and severity of Parkinson's disease based on these visual data [3]. Thus, such classifications can be used in clinical applications as an effective tool for early diagnosis of the disease and monitoring the treatment process.

The study is organized as follows: Section 2 presents a systematic review of the existing literature and a discussion highlighting the research gap. Section 3 describes in detail the deep learning methodology and dataset used. Section 4 contains a comprehensive analysis comparing the proposed model as well as transfer learning models. Finally, Section 5 contains a concluding section summarizing the main findings and conclusions of the study.

II. LITERATURE REVİEW

To improve the diagnosis and treatment of Parkinson's disease, methods that assess motor function, such as the Parkinson's Drawing Test (PDT), are used. The PDT provides information about the stage and severity of the disease by analyzing patients' drawings. In the literature, many studies with Parkinson's Drawing Test (PDT) data have examined the effectiveness of deep learning and in particular convolutional neural network (CNN) architectures.

[4] proposed a Convolutional Neural Network (CNN) based deep learning model for Parkinson's disease diagnosis. The model analyzes handwriting features using dynamic and static spiral tests (DST and SST). The performance is evaluated with K-Fold and Leave-One-Out cross-validation techniques, achieving 88% accuracy. The results show that the combination of both tests is effective in PD diagnosis. In (Martin et al., 2019), a Convolutional Neural Network (CNN) was used for Parkinson's disease (PD) detection. This CNN consists of two parts: feature extraction (convolutional layers) and classification (fully connected layers). The inputs of the CNN are the Fast Fourier Transform module in the frequency range from 0 Hz to 25 Hz. In the study, the discriminative ability of different directions during drawing gestures was analyzed and the best results were obtained in X and Y directions. This analysis was performed using the Digital Graphics Tablet Database of Parkinson's Disease Spiral Drawings. The best results obtained were 96.5% accuracy, 97.7% F1-score and 99.2% area under the curve (AUC).

[5] compared one-, two- and three-dimensional convolutional neural networks (CNNs) to discriminate drawing tests from Parkinson's disease patients and healthy control groups. Using deep learning techniques, dynamic features of the writing signal were combined with static data and feature extraction was performed with CNN models. The novelty of the study is the first application of three-dimensional CNN models in Parkinson's detection. The results show 59.38%, 77.73% and 82.34% accuracy on the DraWritePD dataset and 63.33%, 81.33% and 82.22% accuracy on the PaHaW dataset, respectively. The three-dimensional CNN model shows the highest diagnostic performance in both datasets.

In [6], the effectiveness of transfer learning models for the diagnosis of Parkinson's disease (PD) was investigated. Parkinson's is a neurodegenerative disease that affects normal human movements and the main cause is a lack of dopamine in the brain. PD leads to many additional problems such as sleep disorders, excessive sleepiness, blood pressure fluctuations. In this study, PD was diagnosed with transfer learning models using salient features extracted from Parkinson's disease-specific spiral drawings. VGG19, InceptionV3, ResNet50v2 and DenseNet169 models are evaluated in a comparative analysis for PD detection using handwritten spirals. The results show that the InceptionV3 model achieves 89% accuracy by learning from spiral drawings and demonstrates superior performance with a receiver operating characteristic (ROC) curve value of 95%. These results demonstrate that transfer learning models provide high accuracy in PD diagnosis.

In [7], a handwriting dataset containing 102 spiral drawings was used to predict Parkinson's disease. Data augmentation methods were applied to increase the size of the dataset and various machine learning and deep learning models were trained with the augmented data using pre-trained networks such as RESNET50, VGG16, AlexNet and VGG19. In the performance comparison, the combination model of RESNET-50 and SVM achieved the best results with 98.45% accuracy, 0.99 sensitivity and 0.98 specificity.

In [8], a diagnostic system for Parkinson's disease based on handwritten spiral drawings was developed. Visual information was confirmed to be more effective than dynamic data and the Archimedes spiral dataset was created. Moreover, the CC-Net (Continuous Convolution Network) model extracted various features of handwriting better than traditional networks, achieving high performance metrics such as 89.3% accuracy, MCC 0.733 and AUC 0.934. This system is proposed as a tool that can be applied at home and provide accurate diagnosis.

[9] applied deep convolutional neural networks (CNN) to discriminate Archimedes spiral drawings of Parkinson's patients and healthy controls. The study presents an innovative approach that combines kinetic and pressure features with the shape of the drawn line. Sufficient data set was generated by data augmentation and the trained model showed superior performance compared to shallower classifiers.

In [10], a convolutional neural network (CNN) model utilizing 64x64 pixel hand drawing images was developed to predict Parkinson's disease. With data from 244 PD patients and 228 healthy individuals, the model was trained using KNN-based feature extraction. With a maximum learning rate of 0.001, 97.93% accuracy, 92% precision, 80% sensitivity and 86% F1 score were obtained. These results show that the model can effectively discriminate PD patients from healthy individuals.

In [11], a system was designed using two convolutional neural networks (CNN) to analyze spiral and wave drawings in Parkinson's disease patients. The predictions obtained from the drawings are combined with a metal classifier. Trained with 55 patient data, the model achieved 93.3% accuracy, 94% sensitivity, 93.5% precision and 93.94% F1 score.

[12] examines the state-of-the-art technologies for early diagnosis of Parkinson's Disease (PD). In the study, machine learning-based automatic diagnosis systems and preprocessing and classification stages are discussed. In addition, two experiments were conducted on HandPD and NewHandPD datasets; the first experiment used a hybrid SVM and PCA classification approach, while the second experiment used a modified CNN architecture. The modified CNN achieved better results compared to other methods, reaching 100% accuracy.

In [13], the effect of digital spiral drawings on the classification of Parkinson's Disease (PD) was examined. Using kinematic data from 25 PD patients and 15 healthy individuals, four machine learning classifiers (Logistic Regression, SVC, KNN, Random Forest) were used for classification with 91% accuracy. The results show that digital spiral drawings make a significant contribution to PD diagnosis.

These studies provide important contributions in terms of early diagnosis of Parkinson's disease and monitoring the treatment process and show the potential of deep learning methods in the field of Parkinson's disease. Analyses performed with the Parkinson Drawing Test provide more objective and effective solutions in clinical applications by enabling more precise determination of the stages and severity of the disease.

III. MATERIAL AND METHOD

Classification of digital images has emerged as one of the most important research topics in computer vision and artificial intelligence. Image classification is the process of assigning an image to a specific category and is usually performed using machine learning techniques. In recent years, especially with the development of deep learning algorithms, digital image classification processes have made great progress. One of the most successful methods in this field is convolutional neural networks, known as CNNs. CNNs are known for their ability to automatically learn local features in an image and represent them at a higher level of abstraction. Starting from LeNet-5 proposed by [3], the development has continued with the emergence of deep CNN architectures such as AlexNet [14], VGG [15] and ResNet [16]. These architectures have significantly improved classification accuracy by learning deep features of images.

The advantages of CNNs are that they can learn basic features in images (edges, corners, texture) from low-level to high-level. In addition, sharing the parameters enables more efficient learning and makes it possible to train the model with less data. However, CNNs also have some challenges such as large dataset requirements and long training times. To overcome these problems, Transfer Learning methods are often used. Transfer learning allows a pre-trained model to be retrained for a similar task, resulting in faster learning with less data. This method offers great advantages, especially in areas such as medical images or areas with limited data [17].

Transfer learning architectures typically take models that have been trained on large datasets (e.g. ImageNet) and adapt them for new, smaller datasets. This process allows the model to learn faster and achieve high accuracy with less data. In particular, in a process called fine-tuning, the final layers of the pre-trained network are retrained with a small dataset, thus optimizing the network for specific tasks. In the healthcare field, transfer learning techniques are frequently used to classify digital medical images. The development of CNN architectures and the use of transfer learning has revolutionized the field of digital image classification. These technologies have a wide range of applications not only in the healthcare sector, but also in the security, automotive and entertainment sectors. Significant success has been achieved using deep learning-based image classification methods in tasks such as face recognition, object detection, and environment detection in autonomous vehicles [18].

In this section, we present an innovative approach to perform an effective classification function using the Parkinson Drawing Dataset for early diagnosis of Parkinson's disease. In this context, the dataset used in the study, the proposed new CNN model, the transfer learning architectures and the comparison of these models are explained in detail below.

3.1.Datasets

It provides important contributions to the early diagnosis and monitoring of the treatment process of Parkinson's disease and demonstrates the potential of deep learning methods in the field of Parkinson's disease. The analyses performed with the Parkinson Drawing Test provide more objective and effective solutions in clinical applications by providing a more precise determination of the stages and severity of the disease. The dataset contains two patterns, wave and spiral, and all data are presented in *.png format. The dataset is divided into training and test data. In the training data, there are 72 wave drawings in total, 36 drawn by Parkinson's patients and 36 drawn by healthy individuals. In the test data, there are 30 wave drawings in total, 15 from Parkinson's patients and 15 from healthy individuals. Similarly, there are 72 spiral drawings in total in the training data, 36 belonging to Parkinson's patients and 36 belonging to healthy individuals. In the test data, there are 30 spiral drawings, 15 belonging to Parkinson's patients and 15 belonging to healthy individuals. The dataset does not include any personal information such as age and gender, and no preprocessing was performed on the data. Sample drawings made by Parkinson's patients and healthy individuals are presented in Figure 1, Figure 2, Figure 3 and Figure 4.

Figure1. Examples from the spiral healthy class

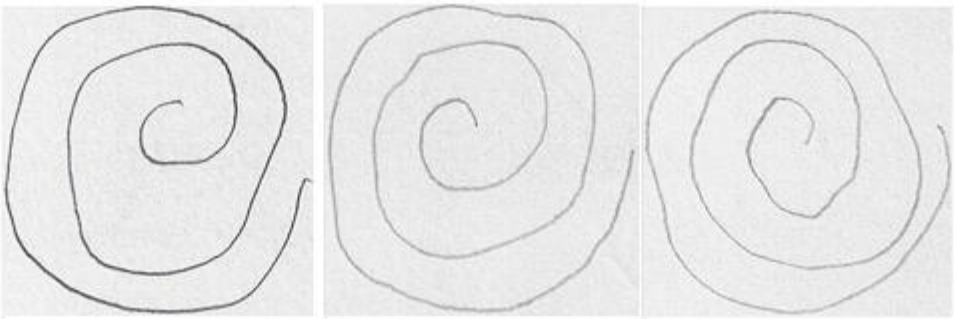


Figure2. Examples from the spiral parkinsonian class

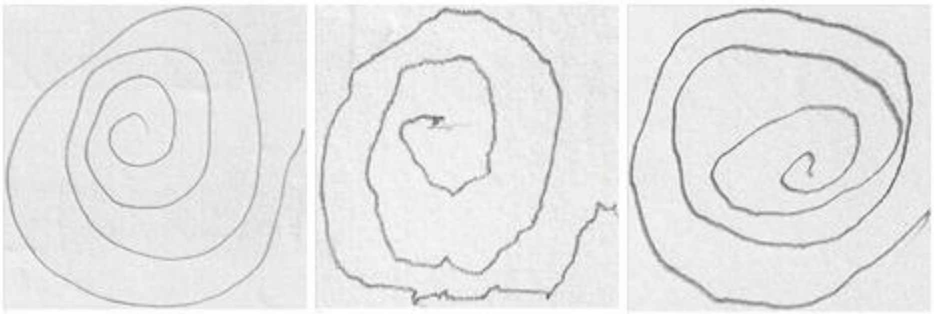


Figure3. Examples from the Wave healthy class

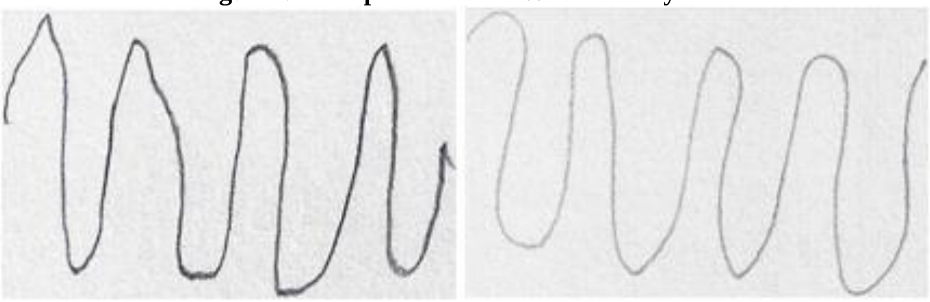
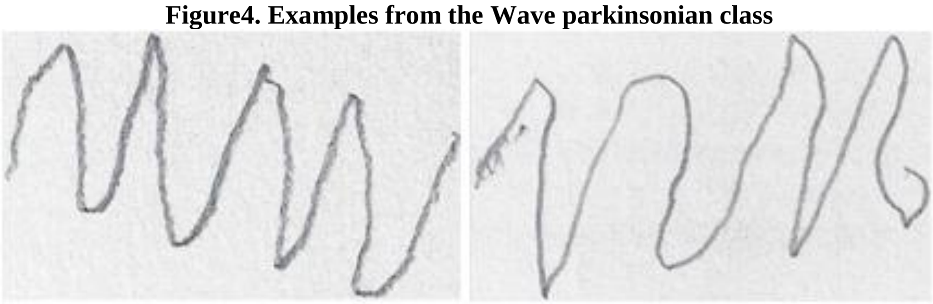


Figure4. Examples from the Wave parkinsonian class



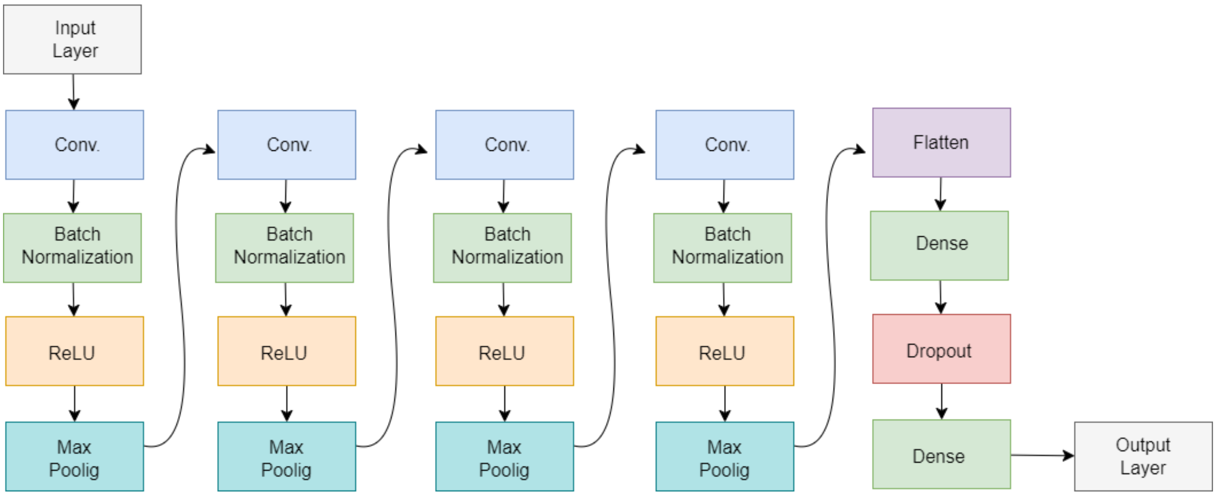
3.2.Model Development

Convolutional neural networks (CNNs) are deep learning architectures that provide high success in image classification tasks and are recognized as one of the most effective tools in this field. CNNs provide a great advantage over traditional methods, especially when working with visual data, thanks to their ability to automatically learn key features in images [3]. By using layered structures to understand the local relationships of pixels in images, these networks begin to recognize more complex features at each layer. The first layers learn simple features such as edges and corners, while later layers recognize higher-level features such as more complex patterns and objects. This feature explains the superiority of CNNs in processing visual data and their ability to classify with high accuracy. Furthermore, the robustness of CNNs to datasets allows them to improve their overall performance by training with large datasets [14]. These advantages in image classification make CNNs widely used in many fields such as health, security, and automotive. In the detection of neurological diseases such as Parkinson's disease, the use of CNNs in tasks such as analyzing drawings of patients' motor functions provides great benefit in obtaining accurate and fast results.

3.2.1. Proposed CNN Model

The CNN architecture developed in this study consists of 22 layers in total, including four convolutional layers. Images are given as input to the first layer of the model. The first convolutional block contains two consecutive 3x3 convolution filters (Conv2D). Both convolution layers are activated by the ReLU (Rectified Linear Unit) activation function. ReLU allows the model to learn non-linear relationships and makes the training process faster and more efficient [19]. After the convolution layers, Batch Normalization was applied. By normalizing the data on each mini-batch, Batch Normalization supports the model to learn faster and more stably, as well as reducing the problems of gradients blowing up or disappearing [20]. The first block is further complemented by the MaxPooling2D layer and the Dropout layer. MaxPooling2D reduces the computational burden of the model by reducing the size of the images and ensures that important features are preserved [21]. The dropout layer disables randomly selected neurons during training to prevent overfitting [22]. The second convolutional block of the model follows a similar structure, allowing deeper features to be learned, and more complex features are learned using 64, 128 and 256 filters, respectively. In the final part of the model, the multidimensional feature maps obtained from the convolutional layers are converted into a single vector with a Flatten layer and then a fully connected structure with a 512-neuron Dense layer. In this layer, overlearning is prevented by using Dropout. As an output layer, a Dense layer is used, which generates probability distributions for 10 classes with Softmax activation. The model is compiled with the Adam optimizer and the multiclass classification error is minimized with the categorical_crossentropy loss function. This structure provides an efficient solution with strong performance in image classification tasks. An image of the proposed CNN model is presented in Figure 5.

Figure 5. Design of the CNN architecture use.



3.2.2. Proposed CNN Model

In classification studies with Parkinson's Drawing Test data, the effectiveness of deep learning models is increased by using transfer learning methods. Transfer learning allows a model trained on large and diverse datasets to be quickly adapted for a new task with limited data. Using this method, convolutional neural network (CNN) architectures are preferred to detect early stages of Parkinson's disease and motor disorders. VGG16 has a deep network structure, allowing more complex features to be learned at each layer. This model can be used effectively in Parkinson's disease diagnosis by successfully learning basic patterns and shapes in visual data [15]. DenseNet169, on the other hand, provides more powerful learning by combining the information from each layer, making it easier to achieve the precision needed to distinguish the stages of Parkinson's disease. DenseNet improves information flow by combining the output of each layer, which allows the model to run more efficiently [23]. MobileNetV2 is characterized by low computing power requirements thanks to its lightweight structure. This feature enables the model to effectively perform Parkinson's disease classification even on mobile devices or systems running with limited resources [24]. ResNet50 improves learning in deep networks by using residual connections. This allows the model to learn more efficiently from deeper layers and is a powerful tool for accurately classifying motor disorders of Parkinson's disease [16]. Finally, EfficientNetB7 stands out as a model that can provide high accuracy with fewer parameters. This architecture can accelerate and optimize classification processes, offering high efficiency and accuracy in the classification of Parkinson's Drawing Test data [25]. These transfer learning models stand out as powerful tools that demonstrate the potential of deep learning in the healthcare field by making important contributions to the early diagnosis and monitoring of the treatment process of Parkinson's disease.

IV. MATERIAL AND METHOD

In recent years, deep learning has been recognized as one of the most widely used and effective approaches to machine learning. Especially in some cognitive tasks, achievements that exceed human performance have led to an increasing preference for deep learning methods. Due to these achievements, deep learning has become an important research topic, especially in critical areas such as healthcare. Studies in the healthcare sector show that deep learning techniques produce outstanding performance outputs and therefore have great potential for early diagnosis of diseases, improving treatment processes and increasing the overall efficiency of healthcare [26]. The success of deep learning applications in healthcare provides a strong indication that this technology will have broader impacts on healthcare in the future [27].

CNN, one of the deep learning methods, has become an important tool in recent years, especially in the diagnosis of diseases. In the field of healthcare, CNNs have achieved great success in detecting subtle differences in medical images and classifying diseases. By automatically extracting features from visual data, these networks can recognize patterns that the human eye cannot recognize. For example, in the diagnosis of skin diseases such as skin cancer, CNNs have demonstrated dermatologist-level success, proving the impact of deep learning in healthcare [26]. In addition, in tasks such as cancer diagnosis and tumor detection, CNNs work effectively on imaging data such as chest X-rays, lung tomography and breast cancer. By accurately distinguishing cancerous cells in medical images, these models increase patients' life chances in the early detection process.

CNNs are also used to diagnose brain diseases, especially neurological diseases such as Parkinson's and Alzheimer's. Brain imaging data such as MRI and PET scans are analyzed by CNNs to detect the early stages of diseases. In the early diagnosis of Parkinson's disease, subtle changes in data such as handwriting analysis and motor skill tests are accurately classified by CNNs. The success of CNNs in healthcare is based on their ability to perform automatic feature extraction in deep layers. This is a crucial advantage, especially when working with large and complex data.

In this study, a CNN architecture is designed to classify drawings of individuals with Parkinson's disease and healthy individuals. The designed CNN model is structured to classify based on spiral and wave drawings made by individuals with Parkinson's disease and healthy individuals.

Then, this CNN architecture is compared with five different transfer learning models used in the study. VGG16, DenseNet169, MobileNetV2, ResNet50 and EfficientNetB7 were used as transfer learning models. Each model was trained and tested to classify drawing data for Parkinson's disease and healthy individuals. The performance metrics obtained for the Wave class are evaluated according to criteria such as accuracy, precision, sensitivity and F1 scores of each model and the results are presented in Table 1.

Table 1. Metrics of the wave class.

Models	True Negative	False Positive	False Negative	True Positive	Accuracy (%)	Recall (%)	Precision (%)	F1-score (%)
EfficientB7	47	4	6	45	90.20	88.24	91.84	90.00
VGG16	45	6	3	48	90.91	94.12	88.89	91.38
Mobilenetvet2	50	1	5	46	94.34	90.20	97.87	93.84
Resnet50	40	11	6	45	82.47	88.24	80.36	84.15
Densenet169	49	2	5	46	93.33	90.20	95.83	92.92
Proposed CNN models	50	1	3	48	96.15	94.12	97.96	96.02

Table 1 compares the performance of the Proposed CNN model designed to classify the drawings of individuals with Parkinson's disease and healthy individuals with five different transfer learning models. The results show that the Proposed CNN model has the highest accuracy, precision, recall and F1 score among all transfer learning models. In particular, Proposed CNN stands out with an accuracy of 96.15%, while the high precision (97.96%) and F1-score (96.02%) values reinforce the model's success in accurately classifying drawings of Parkinson's disease and healthy individuals. Among the other models, MobilenetV2 (accuracy: 94.34%) and Densenet169 (accuracy: 93.33%) gave the closest results, but both models could not fully match the performance of the Proposed CNN. Although VGG16 and EfficientNetB7 also achieved high accuracy rates, the Proposed CNN model was superior in terms of precision and recall. ResNet50, on the other hand, underperformed compared to the other models, lagging behind in accuracy and precision metrics. These findings suggest that the novel CNN architecture may be more effective in Parkinson's disease diagnosis and provide better results compared to transfer learning methods.Especially the high precision and F1-score values indicate that the model is a strong candidate for accurate diagnosis in clinical applications.

The performance metrics obtained for the Spiral class are evaluated according to criteria such as accuracy, precision, sensitivity and F1 scores of each model and the results are presented in Table 2.

Table 2. Classification metrics of the Spiral class.

Models	True Negative	False Positive	False Negative	True Positive	Accuracy (%)	Recall (%)	Precision (%)	F1-score (%)
EfficientB7	45	6	5	46	89.22	90.20	88.46	89.32
VGG16	49	2	8	43	90.20	84.31	95.56	89.67
Mobilenetvet2	44	7	6	45	87.25	88.24	86.54	87.37
Resnet50	42	9	7	44	84.31	86.27	83.02	84.12
Densenet169	46	5	3	48	92.16	94.12	90.57	92.29
Proposed CNN models	48	3	2	49	95.10	96.08	94.23	96.08

Table 2 presents the performance metrics obtained for the Spiral class. According to this table, the Proposed CNN model outperforms all other models in terms of accuracy, recall, precision and F1 score. The Proposed CNN model achieved the highest success with an accuracy of 95.10%. Moreover, the recall value reached a very high rate of 96.08%, indicating that the model has a very good true positive classification rate. It also achieved strong results in Precision and F1-score metrics with 94.23% and 96.08% respectively. This demonstrates the effectiveness of the Proposed CNN model in correctly classifying drawings between Parkinson's disease and healthy individuals. The Densenet169 model is the closest performing model with an accuracy of 92.16%. However, the Proposed CNN performs better in all metrics. Other models, especially VGG16, MobilenetV2 and ResNet50, lagged behind with lower accuracy and recall values. However, VGG16 stands out with its high precision value. In conclusion, the Proposed CNN model stands out as the most successful model in this study with its high performance for the Spiral class. This result shows that the proposed model can be a powerful tool for early diagnosis of Parkinson's disease and accurate classification of healthy individuals.

In Table 3, we systematically summarize the objectives, methods used and results obtained in these studies with the Parkinson Drawing dataset. This comparison provides a clearer picture of the effectiveness and performance of the proposed CNN and transfer learning based models in Parkinson's disease classification. The results obtained contribute to the existing approaches in the field by evaluating the role and accuracy of the proposed CNN model in the early diagnosis of Parkinson's disease.

Table 3. Methodological Approaches and Performance Results for the Parkinson's Drawing domain

Study	Year	Dataset	Method	Accuracy (%)
[28]	2022	Parkinson Drawings	CNN	85
[29]	2023	Archimedean spiral and wave drawing data	CNN (VGG16)	Spiral drawing: 93.34%, Wave drawing: 90%
Proposed CNN Model	2024	Parkinson Drawings	Transfer learning, proposed CNN model	Spiral drawing: 96.08%, Wave drawing: 96.15%

Table 3 compares the accuracy results of different methods used in Parkinson's disease diagnosis. In [28], the CNN-based model achieved 85% accuracy. [29] achieved 93.34% accuracy with spiral plot and 90% accuracy with wave plot in classification with VGG16. The proposed CNN model (2024) achieved 96.08% accuracy with spiral plot and 96.15% accuracy with wave plot using transfer learning. These results show that the proposed model provides higher accuracy rates compared to other studies and is a powerful tool for Parkinson's disease diagnosis.

V. CONCLUSION

In this study, we analyzed the classification results on the drawings of individuals with Parkinson's disease and healthy individuals in Wave and Spiral classes using the Parkinson Drawing Dataset. The proposed CNN model showed superior performance in metrics such as highest accuracy, precision, recall and F1 score for both classes. An accuracy of 96.15% was achieved for the Wave class and 95.10% for the Spiral class. In particular, the Proposed CNN was successful in accurately classifying the drawings of individuals with Parkinson's disease and healthy individuals with high precision (97.96%) and F1-score (96.02%). The Densenet169 model achieved similar results to the Proposed CNN in both classes, but showed a significant superiority in the accuracy and recall values of the Proposed CNN. Other models, especially VGG16, MobileNetV2 and ResNet50, lagged behind with lower accuracy and recall. These findings suggest that the

Proposed CNN model is a more effective tool for the diagnosis of Parkinson's disease in Wave and Spiral classes and for the accurate classification of healthy individuals.

In conclusion, the Proposed CNN model can be used as a potential diagnostic support tool in clinical applications by showing high performance in accurately classifying drawings of Parkinson's disease and healthy individuals. This study shows that the novel CNN architecture provides better results compared to transfer learning methods and makes an important contribution to the early diagnosis of Parkinson's disease.

Conflict of interest
There is no conflict to disclose.

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