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Automated Detection of Parkinson's Disease through Kinematic and Geometric Analysis of Handwritten Strokes using Deep Learning

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Abstract

Parkinson's Disease (PD) is a progressive brain disorder that affects human motor functions. Early Parkinson's Disease (PD) detection plays a major role in facilitating clinical treatment. Handwriting analysis has proven to be an efficient way to detect motor problems; nonetheless, traditional methods have shown poor feature representation capability and classification robustness. In this study, a novel Deep Learning (DL) model based on DenseNet121 for automated detection of PD using spiral and meander handwriting images is introduced. Image processing, hierarchical features extraction, Global Average Pooling technique to produce 2,880-dimensional feature representation, Spatial Dropout technique, and binary classification are included in the proposed methodology. Handwriting benchmark datasets such as PaHaW, HandPD, and NewHandPD are used to test the performance of the proposed framework. The experimental findings show that the presented method is able to achieve 92.8% accuracy, which implies a reliable classification of PD and healthy samples.

Keyword: Parkinson's Disease, Deep Learning, DenseNet121, Handwriting Analysis, Neuro-Biomarker, Spatial Dropout.

1. Introduction

Handwriting assessment allows for the diagnosis of fine motor dysfunction caused by Parkinson's disease, which includes tremors, micrographia, irregular stroke patterns, and lack of coordination. Tasks in the form of Archimedean spirals and square meanders are effective because of its structural patterns, which reveal motor dysfunction. Traditional methods using manually crafted features can be insufficient in reflecting complicated handwriting characteristics. Figure 1 presents the Archimedean spiral and square meander patterns employed to assess handwriting abnormalities associated with PD, including tremor, impaired motor control,

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and reduced movement precision.Since the handwriting distortions that occur due to PD are complex and non-linear, and involve tremor induced oscillations, rigidity-induced irregularities in movements, and stroke continuity differences, they pose a challenge to the existing machine learning methods that rely on hand crafted features. This is because of their limitations in terms of detecting such complex patterns. In order to overcome these challenges, the DenseNet121 model is used owing to its dense connections, efficient propagation of features, and reusing of features. Through hierarchical feature extraction capabilities of DenseNet121, fine spatial representations can be learned, which helps in detecting subtle handwriting abnormalities.

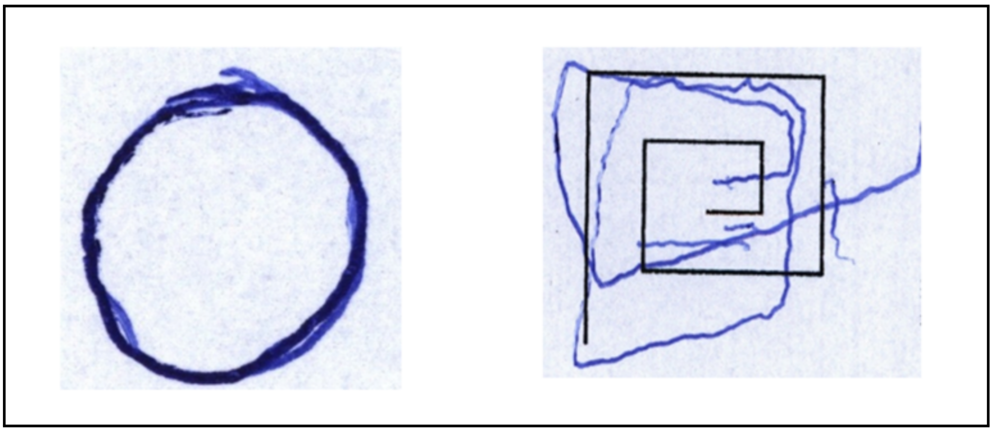

Figure 1. Standardized and writing patterns used for parkinson's disease detection.

Through the use of deep learning feature extraction from standard drawing tasks, this research strives to develop an objective, scalable, and clinically practical method for diagnosing PD. Apart from helping with early detection of PD, this methodology will provide the means to monitor its progression through handwriting analysis.

2. Literature Survey

Recent progress in artificial intelligence has been instrumental in improving the diagnosis of Parkinson's disease (PD) through automated analysis of neurological and motor dysfunctions. Structural changes of the connectivity in brain networks were studied by Bergamino et al. [1], whereas Akgüller et al. [2] used machine learning and information theory to study changes in brain networks' functional characteristics in connection with PD. Topological changes in structural brain networks were analyzed by Ge et al. [3], which showed the value of graph-based markers in characterizing the disease. An extensive review article by Lamba et al. [5] outlined recent fast development of machine learning and deep learning methods for PD diagnostics and their increased clinical relevance. Likewise, Islam et al. [8] reviewed PD diagnoses using handwriting and voice recordings, and demonstrated that deep learning methods surpass classical machine learning approaches in PD diagnosis.

The analysis of handwriting has become a successful non-invasive method for detecting motor abnormalities in patients suffering from Parkinson's disease. Sivaranjini and Sujatha [7] have shown that CNNs extract discriminative handwriting features automatically, without using hand-crafted features. Naz et al. [4] developed a multi-model CNN-based fusion method that combines complementary handwriting representations. Aldhyani et al. [9] have used the spiral and wave handwriting patterns within the deep learning framework, showing that geometric handwriting can successfully detect tremor and movement irregularities related to Parkinson's disease. Taleb et al. [10] have studied the performance of various deep learning models for handwriting recognition and have shown that the use of deep feature extraction gives better results than traditional classifiers. Recently, Allebawi et al. [6] have proposed an offline handwriting system based on the SqueezeNet and TinySiamese networks, showing that lightweight deep learning architectures can be successfully used for Parkinson's disease detection. The application of transfer learning has been found to be one of the effective approaches used to enhance the performance of diagnoses based on handwriting images in situations where there is insufficient data. The approach was proposed by Dogan [11] whereby a hybrid of CNN, NCA and SVM was designed to provide deep features that are extracted through the use of the Neighborhood Component Analysis (NCA) and the Support Vector Machine (SVM). Liang et al. [12] presented the design of Vision Transformer transfer learning model which is used to detect handwriting images that have long-range spatial relations.

2.1 Advanced Deep Learning Architectures

The recent works have emphasized developing efficient computation models without any reduction in the classification ability by using new network architectures. The work done by Özdemir and Özyurt [14] has used ElasticNet feature selection and vision transformers to minimize redundancy in feature representation and improve discriminatory power. Similarly, Pechetti and Rao [15] have developed an efficient MobileNetV3 model along with feature attention and optimization algorithms, which performed well in diagnosis with low computational costs. Raajasree and Jaichandran [16] have presented an enhanced EfficientNet-based multi-modal framework by combining optimized feature extraction and hybrid optimization techniques for the diagnosis of PD. In addition to it, Sangeetha and Umarani [17] have used Deep Maxout Fuzzy EfficientNet model for MRI-based PD diagnosis.

2.2 Research Gaps and Motivation

Despite advances in AI-based PD detection, existing studies largely focus on classification performance while providing limited analysis of the hierarchical visual features associated with Parkinsonian handwriting. Handwriting solutions based on conventional methods usually make use of hand-engineered features, while more recent transfer learning and transformers require even higher computational power. In addition, little research has been done concerning the extraction and interpretation of feature representations for standardized geometric handwriting. The connection between low-level stroke boundaries, texture changes, and other handwriting features at higher levels is also not fully explored. This problem becomes the motivation for developing the architecture based on DenseNet121 which makes use of hierarchical feature extraction, Global Average Pooling, and Spatial Dropout techniques.

3. Proposed Methodology

3.1 System Architecture

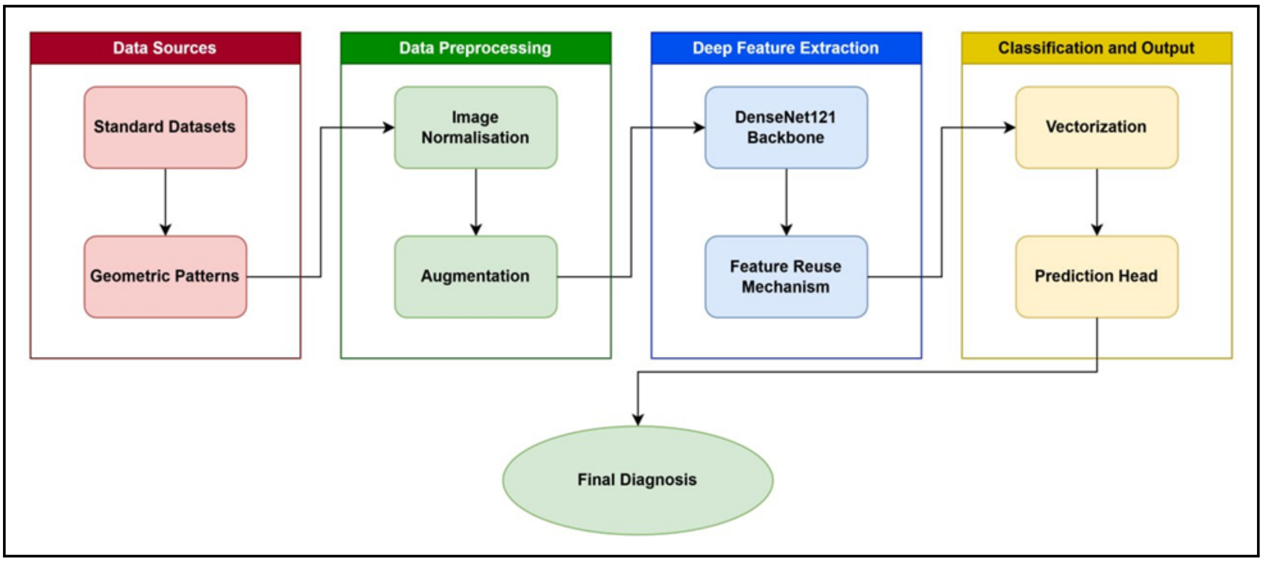

Figure 2. Proposed DenseNet121-based framework

Figure 2 shows the complete process flowchart of the suggested methodology starting from image acquisition and preprocessing, DenseNet121-based feature extraction, feature regularization, and finally classification of PD. The proposed methodology uses deep learning using DenseNet121 model to automatically detect PD from offline handwriting images. And the proposed framework is composed of dataset collection, image preprocessing, deep feature extraction, feature regularization, and classification. Feature learning at different levels is used to extract distinctive features related to PD, whereas spatial dropout contributes towards better generalization.

3.2 Dataset Description

The proposed framework utilizes three handwriting datasets, which are openly accessible and include PaHaW (Parkinson's Handwriting Database), HandPD and NewHandPD used for the automatic identification of PD.

Table 1. Characteristics of the handwriting datasets

Dataset	PD Subjects	Healthy Controls	Total Subjects	Handwriting Tasks	Data Format
[18]	37	38	75	Spiral, Meander, Words, Sentences	Offline handwriting
[19]	46	46	92	Spiral, Meander	Offline handwriting
[20]	46	46	92	Spiral, Meander	Offline and online handwriting

The characteristics of the handwriting datasets employed in this study are summarized in Table 1. The number of subjects is the number of participants included in each particular dataset while the classification of images was performed at the handwriting image level. Samples of Archimedean spiral and square meander from the datasets were selected and united to get the dataset for image classification. The dataset was then split to obtain the training and testing datasets for DenseNet121.

3.3 Data Preprocessing

The hand-written data sets are preprocessed to be consistent and compatible with the proposed classification scheme using the DenseNet121. First, the hand-written images of spiral and meander are examined to eliminate any corrupted datasets that would have negative impacts on the learning process. All images are then resized to the resolution of 224 x 224 pixels, in accordance with the requirements of the DenseNet121 input while maintaining the structural features of the handwriting strokes. Normalization of pixel intensity values is performed next to achieve numerical stability for the training process.

In order to enhance the model's generalization performance, data augmentation approaches are adopted in the training process. Random geometric transformations such as random translation along both horizontal and vertical directions, random rotation, zoom, and shear are used to create different variations of handwriting while maintaining the underlying motion characteristics linked with PD. Data augmentation helps prevent overfitting through providing realistic handwriting variations to the network and makes it possible to extract robust spatial features. The processed and augmented handwriting images are finally transformed into input tensors and fed into the DenseNet121 model.

3.4 DenseNet121-Based Feature Extraction

After preprocessing, the standardized handwriting samples are fed into the DenseNet121 model for hierarchical deep feature extraction. The DenseNet121 model is chosen based on its dense connectivity, which means that at every convolutional layer, the feature maps are collected from all previous layers through direct connections. The benefits of this type of architecture include feature reuse, improved gradient flow, and prevention of the vanishing gradient problem, thus making it possible to learn the discriminative handwriting representations. In this way, both low-level features like strokes' edges and higher-level semantics related to the Parkinsonian handwriting can be extracted.

DenseNet121 model has an initial convolution layer, followed by four dense blocks, separated by transition layers, and finally a Global Average Pooling layer. In a dense block, the output of the l^{th} layer is calculated by concatenation of the feature maps produced by all previous layers, which can be expressed as

$$x_l = H_l\left([x_0, x_1, x_2, \ldots, x_{l-1}]\right) \tag{1}$$

where x_l represents the output feature map of the l^{th} layer, [ ] denotes the concatenation operation, and $H_l(\cdot)$ represents the composite function consisting of Batch Normalization, Rectified Linear Unit, and convolution operations. This dense feature propagation enhances information flow across the network while reducing redundant feature learning.

The final convolutional feature maps are converted to the compressed form of features by applying Global Average Pooling technique to get a 2,880-dimensional vector that encapsulates the most informative aspects of spatial information while greatly reducing the number of trainable parameters. The deep feature vectors are then used as the input to the next classification layer.

3.5 Regularization Using Spatial Dropout

Spatial Dropout is used as a regularization method after analyzing the handwriting features in order to enhance the generalization ability of the developed DenseNet121 model. As opposed to the standard dropout which randomly turns off single neurons, Spatial Dropout removes whole feature maps during training. Such approach helps avoid high dependence on some activation channels and forces the model to learn more discriminative feature representations. Thus, the possibility of overfitting is avoided while spatial dependencies between the extracted features are retained.

Let the extracted feature tensor be represented as

$$F \in \mathbb{R}^{H \times W \times C} \tag{2}$$

where H denote the height, W denote the width and C denote the number of feature channels. A binary mask is generated independently for each feature channel as

$$m_c \sim \text{Bernoulli}(1-p), \quad c = 1,2,\ldots,C \tag{3}$$

where p represents the dropout probability and m_c is the binary mask corresponding to the c^{th} feature channel. The output feature tensor after Spatial Dropout is computed as

$$\widehat{F}_{(:,:,c)} = \frac{m_c}{1-p} F_{(:,:,c)} \tag{4}$$

where $\widehat{F}$ denotes the regularized feature tensor. During the training process, random deactivation of feature maps occurs while all feature maps are kept active throughout inference. This form of regularization helps in ensuring that the representation learning process produces more robust features, allowing the model to become more generalizable to handwriting data samples collected from various benchmark datasets. These regularized feature maps are then passed on to the Global Average Pooling and classification layers to predict PD.

3.6 Classification and Optimization Strategy

Regularized deep feature representations learned by the DenseNet121 model are passed on to a fully connected classification layer in order to classify the PD. The feature vectors are converted into class probabilities using a sigmoid activation function, hence formulating the problem as a binary classification problem, where PD is distinguished from HC handwriting samples. The predicted probability for the positive class is computed as

$$\widehat{y} = \sigma(Wx + b) \tag{5}$$

where x denotes the extracted feature vector, W and b represent the trainable weight matrix and bias term of the classification layer, respectively, and $\sigma(\cdot)$ is the sigmoid activation function defined as

$$\sigma(z) = \frac{1}{1+e^{-z}} \tag{6}$$

The optimization process is carried out using the adaptive momentum (Adam) optimizer that sets an adaptive learning rate for each training parameter to ensure stable convergence. The binary cross-entropy (BCE) loss function is used to minimize the difference between the estimated probabilities and the true labels. The BCE loss function is expressed as

$$L = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i \log(\widehat{y}_i) + (1-y_i)\log(1-\widehat{y}_i)\right] \tag{7}$$

where N denotes the total number of training samples, y_i represents the ground-truth class label, and $\widehat{y}_i$ corresponds to the predicted probability for the i^{th} sample. In the training process, the network adjusts its weights by minimizing loss while maximizing the efficiency of classification.

4. Results and Discussion

The efficiency of the proposed DenseNet121 based framework is tested on benchmark handwriting datasets consisting of handwriting samples of PD patients and normal individuals. The experiment examines the ability of the proposed architecture to extract discriminative handwriting features using deep learning techniques. The performance is analyzed using evaluation measures and confusion matrix to verify the robustness and reliability of the proposed approach.

4.1 Experimental Setup

This proposed framework was implemented through the use of the Python programming language and its deep learning libraries TensorFlow and Keras. The experiment design is briefly illustrated in Table 2 below. The training of DenseNet121 was done using the Adam optimization algorithm and Binary Cross-Entropy Loss function for classification of the PD and healthy control handwritten characters. The handwritten images used were split into training and testing data, where 375 images were separated for the testing process. The test data comprised 205 healthy controls and 170 PD data.

Table 2. Experimental configuration of the proposed DenseNet121 framework

Parameter	**Configuration**
Programming Language	Python
Deep Learning Framework	TensorFlow, Keras
Backbone Network	DenseNet121
Input Image Size	224 × 224 pixels
Loss Function	Binary Cross-Entropy
Batch Size	32
Learning Rate	0.001
Classification Type	Binary (Parkinson's Disease / Healthy Control)

4.2 Deep Feature Representation Analysis

The DenseNet121 model creates high-dimensional feature vectors, which contain discriminatory features of handwriting that relate to PD. These convolutional features, obtained after dense blocks and transition layers, are then pooled through the Global Average Pooling (GAP) layer to form a compact feature vector of 2,880 dimensions per sample of handwriting.

	f0	f1	f2	f3	f4	f5	f6	\
0	0.095885	0.037789	0.039325	0.058641	0.075196	0.067638	0.149176	
1	0.095630	0.038771	0.036761	0.060454	0.078955	0.068922	0.160330	
2	0.095710	0.038594	0.036453	0.062450	0.080826	0.067239	0.185594	
3	0.095189	0.037851	0.036245	0.062444	0.079467	0.066859	0.187084	
4	0.095447	0.038681	0.038129	0.060412	0.077955	0.067071	0.165729	

	f7	f8	f9	...	f2872	f2873	f2874	f2875	\
0	0.037383	0.0	0.105954	...	-0.002978	0.021195	0.005707	0.021909	
1	0.037921	0.0	0.103414	...	0.005929	0.013149	-0.009467	-0.000523	
2	0.037301	0.0	0.100601	...	-0.007334	0.008555	0.021068	0.010539	
3	0.036959	0.0	0.100609	...	0.000085	0.016455	-0.012394	0.017705	
4	0.037897	0.0	0.103481	...	0.018772	0.021887	-0.002065	0.001404	

	f2876	f2877	f2878	f2879	label	\
0	0.007625	0.060687	0.000797	-0.019914	parkinson_meander	
1	0.018787	0.069827	0.002181	-0.021381	parkinson_meander	
2	0.013995	0.091694	0.009808	-0.022114	parkinson_meander	
3	-0.007247	0.065580	0.000436	-0.025501	parkinson_meander	
4	0.019003	0.046903	0.001259	-0.014186	parkinson_meander	

Figure 3. Standardized and writing patterns used for parkinson's disease detection.

Figure 3 provides the illustration of the kinematic feature vectors. The components of the feature vectors are the activations that are learned using the DenseNet121 model. The capability of the neural network model to extract hierarchical representations of the handwriting images is demonstrated by the activations. While only the activations for a selected number of features are included in the visualization, the total number of the features is 2,880, which gives a detailed description of the handwriting features.

4.3 Hierarchical Feature Learning Analysis

To explore the hierarchy of learning ability of the proposed architecture DenseNet121, the visualized feature maps derived from different layers of convolution are considered. The feature maps give an understanding of how the network converts the input raw handwriting data into a discriminative representation for performing the classification task of PD diagnosis. With increasing depth of the network, the derived features become complex semantic representations from simple visual representations.

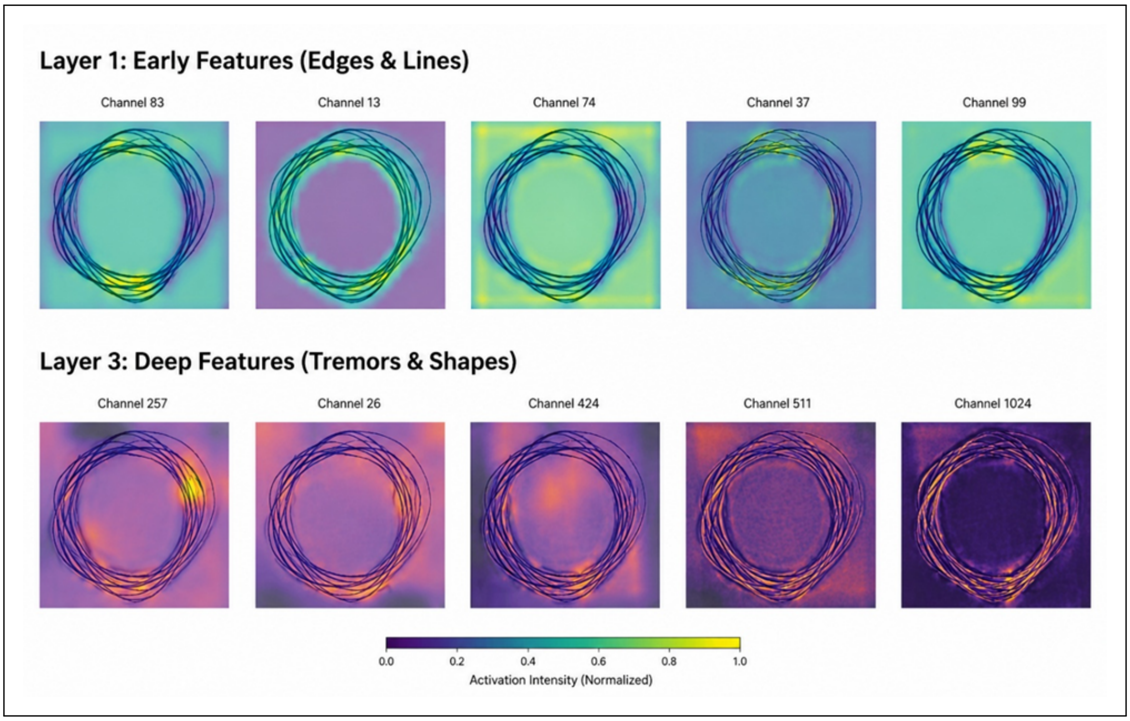

Figure 4. Representative feature maps generated by the proposed DenseNet121 framework.

As shown in Figure 4, the figure shows some of the representative feature maps that have been generated by the convolutional layers of the proposed DenseNet121. As observed, the first few layers focus on the extraction of basic characteristics in an image, such as edges, stroke borders, and variations in textures. On the other hand, the deeper layers focus on the extraction of higher-level structural information such as strokes' curvatures, continuity, and unique handwriting patterns associated with the presence of PD. This process indicates how dense connections in the proposed framework help in reusing of the extracted features.

4.4 Classification Performance Analysis

Table 3. Classification performance of the proposed DenseNet121 framework

Performance Metric	Value (%)
Accuracy	92.80
Precision	93.33
Recall	90.59
F1-Score	91.94

The experimental results (Table 3) have proven that the architecture of DenseNet121 is able to capture handwriting patterns specific for certain diseases, providing good classification performance in terms of all used evaluation metrics. The developed framework provides stable and reliable performance for automated PD detection based on handwriting images.

4.5 Confusion Matrix Analysis

The classification performance of the suggested DenseNet121 model is analyzed through the use of the confusion matrix provided in Figure 5. There are 375 test samples in the matrix with 194 samples of healthy controls and 154 samples of PD correctly classified. In addition, the proposed model misclassifies 11 samples of healthy controls as PD and 16 samples of PD as healthy controls. The fact that the number of misclassification cases is quite low shows that the model successfully separates the two classes of handwriting.

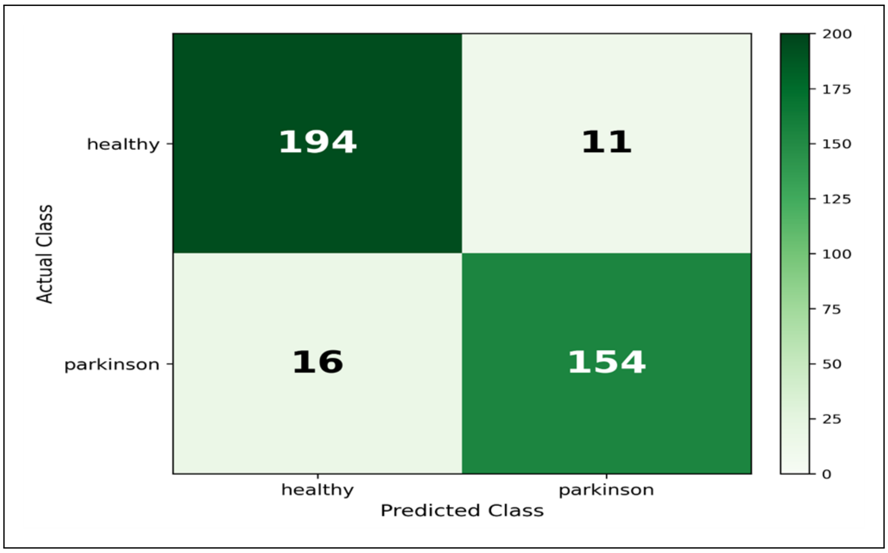

Figure 5. Confusion matrix of the proposed DenseNet121 framework

From the confusion matrix, it is clear that the proposed approach ensures consistency in recognition among both classes with reduced number of false recognized samples. The results show that the feature representations obtained from DenseNet121 are able to offer enough discriminative power for discriminating between handwriting patterns of patients suffering from PD and those of healthy people.

5. Conclusion

This research presented a DenseNet121-based deep learning framework for the automated detection of Parkinson's disease using handwritten spiral and meander images. The proposed deep learning architecture uses the standard process of data pre-processing, deep feature extraction, Spatial Dropout regularization, and binary classification for the automatic identification of handwriting abnormalities due to Parkinson's disease. The use of deep feature representations obtained from deep learning helps in differentiating between Parkinson's disease and normal control samples, showing the efficacy of the proposed method in handwriting-based diagnosis. The experiment confirms that the proposed architecture gives robust and consistent classification results along with improved feature learning. In future, this research work could be extended to the incorporation of multimodal data such as speech and gait for further improving the classification results. In addition, the lightweight deep learning architectures and explainable artificial intelligence approaches would also be explored.

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