Journal of Innovative Image Processing (ISSN: 2582-4252)
www.irojournals.com/iroiip/

PDCNet: Parkinson's Disease Classification Network using MRI Scans

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Abstract

Parkinson's Disease (PD) is a neurodegenerative condition in which timely and precise diagnosis is essential for optimal care. A Convolutional Neural Networks (CNNs) architecture, PDCNet is designed to classify PD from Magnetic Resonance Imaging (MRI) scans sourced from the NTUA Parkinson dataset. The PDCNet has three convolution layers with different numbers of filters and two fully connected layers with efficient Gradient-weighted Class Activation Mapping (Grad-CAM) to improve generalization and mitigate overfitting. The proposed PDCNet uses different dropout ratios which provides the benefits of regularization without compromising predictive performance. The proposed PDCNet has a remarkable classification accuracy of 98.27%, with a sensitivity of 97.69% and specificity of 98.85% when using 10000 images of NTUA dataset for each class (normal and PD). The experimental results emphasize the capability of PDCNet with other deep learning architectures such as VGG, ResNet, and deep belief networks for non-invasive PD classification using MRI data. The study's findings indicate that integrating AI-driven diagnostics into clinical workflows may

DOI: https://doi.org/10.36548/jiip.2025.1.010
Received:04.03.2025, received in revised form: 01.04.2025, accepted:14.04.2025, published: 25.04.2025

enhance early identification andKattankulathur individualised therapy planning for individuals with PD.

Keywords: Parkinson's Disease, MRI, Early Diagnosis, Clinical Applications, Convolutional Neural Networks.

1. Introduction

The accurate diagnosis of any medical condition in its initial stages is essential for effective therapy [1-3]. PD is a neurological condition that often impairs motor functions. The research advocates for using a deep belief network (DBN) approach, recognized as an advanced ML algorithm that functions primarily as a memory structure, enabling deep and hierarchical learning. It emphasizes the significance of spiral designs in monitoring the progression of PD over time [4]. It uses advanced analytical software and ML to assess datasets. Boosting algorithms, a prevalent ML technique, extract insights from complex datasets. This research presents an adaptive sparse learning approach for the early identification of PD, including multimodal data and labelling [5]. The approach uses similarity learning and feature selection, improving other approaches in classifying and medical score regression. Neuropsychological assessments, including patient drawings, may assist in diagnosing the condition [6]. A model using VGG-16 and VGG-19 incorporates wave and spiral inputs. The technique for examining wave train electrical activity, concentrating on local maxima, has been used to investigate epilepsy discharges and human electroencephalographic signals and has been employed for the differential diagnosis of neurodegenerative disorders such as PD and essential tremors [7]. The proposal involves a wearable device that captures movement characteristics in persons with PD and healthy subjects, allowing precise recognition of motor patterns and evaluations of symptom severity [8].

PD is a progressive neurological disorder that affects the elderly, requiring early diagnosis for successful intervention [9]. The comparative analysis assesses model efficacy and interpretability methodologies and examines the significance of face characteristics in diagnosing PD using static images, emphasizing the identification of hypomimia [10]. It examines the implementation of voice-based biomarkers for predicting the development of PD through ML methodologies [11]. The results distinguish between PD patients and healthy persons, emphasizing the potential beneficial effects of voice-based biomarkers.

It introduces Heterogeneous broad balanced domain adaptation, a new domain adaptation technique designed to fix the problem of feature space inconsistency in PD speech data [12]. The key to getting medical assistance quickly is early diagnosis [13]. Artificial intelligence (AI) created a powerful computer-assisted technique for PD diagnosis utilizing spiral and wave diagrams. Conventional SVM algorithms for predicting PD onset exhibit difficulties in handling image data, rendering them inadequate for precise diagnosis, such as MRI scans, a challenge that the ResNet-101 deep learning method overcomes [14]. Contributing substantially to the scientific community investigates the potential use of game-based evaluations in diagnosing PD.

The class imbalance learning approach to enhance the accuracy of ML models for PD diagnosis [15]. The physical and neurological symptoms of PD deteriorate with time. Since PD is like other conditions, such as aging and tremor, making a diagnosis may be difficult [16]. An extensive overview of several DL algorithms used for PD diagnosis, to identify the PSD using a CNN method that is built on VGG16 [17]. Features may be extracted from PET scan images automatically. To identify PD patients from healthy persons using a CNN [18]. The AlexNet CNN trains and tests using deep learning. 3D CNN only used structural brain images for their training to identify Parkinson's disease [19]. To combine MRI and demographic data to forecast the progression of PD [20]. A Reinforcement Learning-based medication adjustment network is used to mimic the effects of a doctor-prescribed drug. The method improves the accuracy of both motor and non-motor predictions, which bodes well for predicting the course of PD over a longer period.

The efficacy of ML algorithms in identifying 8.5 million individuals globally who suffer from PD is examined [21]. Characteristics of the neurological disorder known as PD include tremors, rigidity, and irregularities in voice production [22]. Decreased dopamine levels cause PD, which manifests in old age. Delaying PD production may be achieved by early prediction [23]. Using Kaggle datasets that include both normal cases and PD patients, this study uses five ML models to aid in the early identification of PD. One way to slow down the course of PD is by early prediction. PD can be detected at an early stage using Artificial Neural Networks (ANN) and upgraded k-nearest Neighbour (kNN) methods [24]. It shows that speech recordings made with smartphones and augmented with ML may correctly identify people with PD [25]. The prevalent neurological disorder known as PD currently has no treatment or recognized cause [26], which makes early diagnosis difficult for healthcare practitioners,

despite being critical for symptom management. AI and other computer-aided solutions may be more efficient than brain imaging tests. The extraction of features from image datasets, especially those including scale and rotation invariance, has yet to be the subject of comparative analysis.

The speech recordings made with smartphones and augmented with ML may correctly identify people with PD [27]. Optimal feature subset selection, segmentation, and preprocessing are all steps in the process. BCI applications utilizing EEG signals are discussed in [28], which uses signal processing techniques and nearest neighbour classification. Patient data from the UCI ML Repository can be used to create ML algorithms that can diagnose and assess PD [29]. Finding common features across Parkinsonian characteristics is the goal of this study, which uses data collection, exploratory analysis, and visualization techniques. Precise data preparation and patient treatment rely on the Minority Random Oversampling approach. Graph Convolutional Networks and graph building based on Euclidean distance are introduced as a new method for PD classification [30]. Using a combination of facial expressions that convey different emotions proposes a new way to diagnose auto PD [31]. Prompt treatment and prevention of disorders depend on early diagnosis. There is currently no understanding of what causes or cures PD, [32]. Challenges such as an absence of attention-based models, models trained on hand-drawn datasets, and robust vision transformers that have been pre-trained are present.

This study is motivated by the need for precise and non-invasive techniques to identify PD at an early stage. Modern diagnostic methods are limited by subjectivity and need specialised knowledge. This work mitigates these deficiencies by using deep learning with MRI images, providing a more automated, accurate, and scalable approach for PD classification. PD is a progressive neurological condition without a definite diagnostic test, resulting in delayed or erroneous diagnosis. Traditional diagnostic techniques depend on clinical manifestations, which may emerge in later stages. This research focuses on the need for early and precise identification of PD by non-invasive methods and presents a high-performance PDCNet for the identification of PD using MRI data from the NTUA Parkinson dataset. This research significantly develops a robust AI-driven framework for PD identification using CNN and MRI data. It provides a scalable, non-invasive technology that smoothly integrates into healthcare environments, allowing for early intervention and personalised treatment options for PD patients.

2. Methods and Materials

The proposed work introduces PDCNet, a CNN model for the classification of PD utilising MRI scans, which integrates sophisticated regularisation methods and Grad-CAM, demonstrating outstanding performance and improving traditional deep learning frameworks in non-invasive PD diagnosis. The proposed PDCNet for PD identification using MRI images is shown in Figure 1. The features for PD are extracted using convolutional and pooling layers and are classified using fully connected layers. The proposed PDCNet is specifically designed for early PD detection in clinical settings and achieves excellent accuracy.

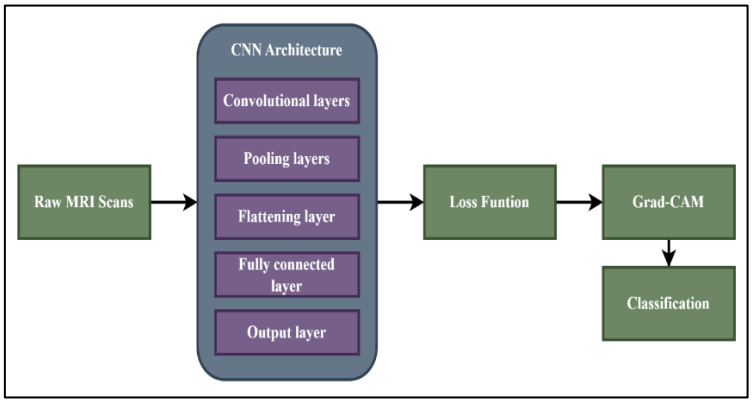

Figure 1. Workflow of the CNN Model for Early PD Diagnosis

Figure 2 shows the proposed PDCNet architecture for detecting PD using MRI data. The feature extraction technique starts with an input layer that receives the MRI images of PD patients as well as normal patients. Then, three convolutional blocks, including Conv2D and MaxPooling2D, are used. For classification, the obtained features are flattened in the flattening layer before being input into the fully connected layers with different dropout ratios. For binary classification (PD/healthy), the output layer uses Softmax. The Grad-CAM in the fully connected layer ensures the interpretability of PD and healthy images efficiently.

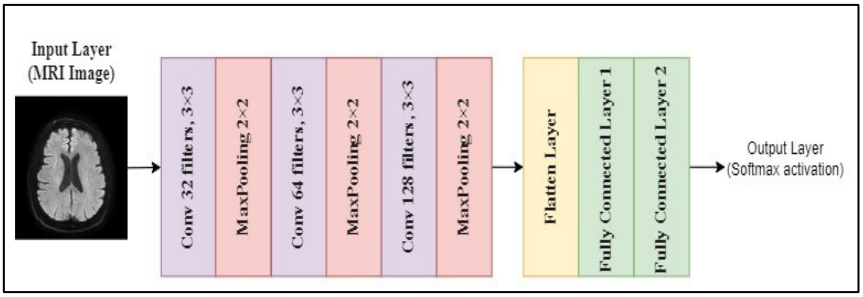

Figure 2. Proposed PDCNet Architecture for PD Detection using MRI Scans

Three convolutional blocks make up the PDCNet architecture, and they process the input image using different sets of learnable filters (kernels). This method makes use of a 3×3 kernel filter size, which is often used for detecting local patterns like textures and edges. There are 32 filters in the first convolutional layer, 64 in the second, and 128 in the third. To add non-linearity, each layer uses the convolution process and then a ReLU activation function. In mathematics, the convolution operation is expressed as:

$$Feature\ Map(i,j) = \sum_{m=0}^{k-1}\sum_{n=0}^{k-1} Input(i+m, j+n) \cdot Kernel(m,n) + Bias \qquad (1)$$

where Input(i,j) denotes the pixel of the input image located at coordinates (i,j), Kernel(m,n) represents the filter/kernel of dimensions k × k, and Bias is a parameter that can be learnt. Figure 3 shows the feature maps obtained from the convolution layer.

Figure 3. Feature Map from PDCNet

The convolution procedure is succeeded by a Rectified Linear Unit (ReLU) activation function, which adds non-linearity by producing the greater value between zero and the input. Figure 4 shows that the ReLU activation function yields 0 for negative inputs and x for positive inputs, facilitating efficient learning by averting vanishing gradients while preserving computational simplicity in deep neural networks.

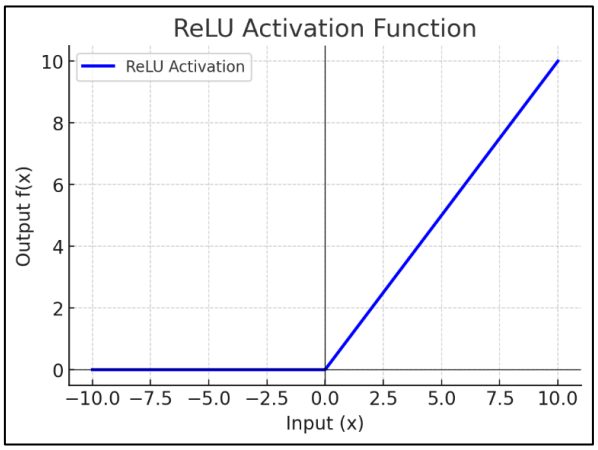

Figure 4. ReLU Activation Function: Non-Linearity in Deep Learning

This enables the model to discern complex patterns within the data. To reduce the feature maps spatial dimensions after convolution while keeping the most relevant characteristics, max pooling layers are used for down-sampling. This approach uses a 2×2 pool size, which cuts the size of the feature map in half. Max pooling is defined as:

$$Output(i,j) = \underset{m,n \in Window}{max} Input\ (i+m, j+n) \tag{2}$$

The computational complexity is reduced, and the most important characteristics are focused on in this stage. The convolutional and pooling layers provide feature maps, which are then transformed into a 1D vector and fed into fully connected layers. For example, if the input is to be classified as PD or healthy, these layers will integrate the collected information to provide a final prediction. A Softmax activation function is used on the output of the fully connected layers to transform the scores into probabilities for each class, defined as:

$$Softmax(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{C} e^{z_j}} \tag{3}$$

where C is the number of classes (such as PD or healthy), and z_i is the output score for classes I and C. Dropout is a regularisation method used to mitigate overfitting in neural networks. During training, it randomly disables a fraction of neurons in a layer, compelling the network to acquire more resilient and redundant features. The inverted scaling preserves the anticipated total of activations during training. As a measure of the discrepancy between the actual labels and the predicted probabilities, the Cross-Entropy Loss function [33] is used to train the model expressed as:

$$Loss = -\sum_{i=1}^{C} y_i \log(\hat{y}_i) \quad (4)$$

where y_i is a true label, c is the number of classes, and $\hat{y}_i$ the predicted probability . For updating the model parameters and minimising loss, the Adam optimiser is given by:

$$\theta_{t+1} = \theta_t - \eta \cdot \frac{\hat{m}_t}{\sqrt{\hat{v}_t + \epsilon}} \quad (5)$$

where θ_t represents the model parameters at step t, η is the learning rate (0.001), $\hat{m}_t$ and $\hat{v}_t$ Bias-adjusted estimations of the initial and secondary moments of the gradients. Table 1 shows the parameters of the PDCNet model. These parameters provide efficient feature extraction, classification, and training for precise identification of PD using MRI data from the NTUA Parkinson dataset. Table 1 below shows the CNN model parameters for PD detection.

Table 1. CNN Model Parameters for PD Detection

Parameter	**Value**
Input Shape	128 × 128 × (Grayscale)
Convolutional Layers	3
Kernel Size	3 × 3
Filters	32, 64, 128
Pooling	Max Pooling (2 × 2)
Activation Function	ReLU
No of Fully Connected Layers	2
Output Layer	2 units (Softmax)
Loss Function	Cross-Entropy Loss

3. Results and Discussion

The study used a carefully selected subset of the extensive NTUA Parkinson Database [34-35], including 43,087 MRI scans (32,706 from PD patients and 10,381 from healthy). Training the model on MRI images may need between 12 to 48 hours on a high-performance GPU. The inference duration for each MRI scan is around 1–3 seconds on a GPU, facilitating

quick classification. The model's inference time of 1–3 seconds per scan, 98.27% accuracy, and GPU optimisation make it appropriate for real-time, scalable, and dependable classification of PD in clinical environments.

Figure 5 shows the MRI images of PD patients in the NTUA Parkinson dataset. These images exhibit anatomical alterations, including atrophy in the substantia nigra and basal ganglia, which are essential for motor regulation. These images are used to train the CNN model for precise PD classification.

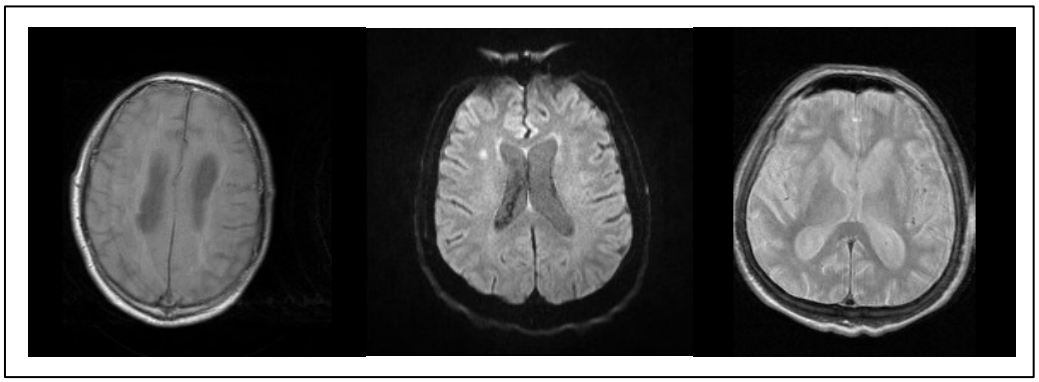

Figure 5. MRI Scan from NTUA Parkinson Dataset Showing PD-Affected Brain Regions

Figure 6 shows the MRI images of non-PD patients in the NTUA Parkinson dataset, revealing no notable structural abnormalities in brain areas such as the substantia nigra or basal ganglia. These images help the PDCNet model in differentiating between healthy and PD-affected brains, providing accurate classification and strong performance in PD diagnosis.

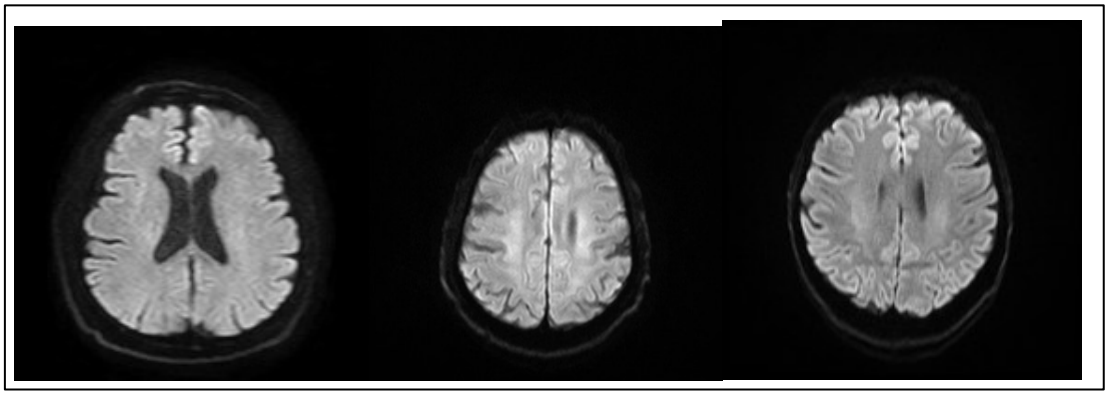

Figure 6. MRI Scan of a Healthy Person from NTUA Parkinson Dataset

To provide an equitable model for training and prevent algorithmic bias favouring the predominant PD cases, the researchers used a stratified sample of 10,000 images, consisting of

10,000 PD patient scans randomly picked from the accessible pool and 10,000 non-PD control images. This balanced 1:1 ratio allows the CNN model to acquire differentiating characteristics without being influenced by class imbalance. Utilising this representative sample instead of the whole unbalanced dataset, the research achieves more dependable performance metrics while preserving clinical significance. The images are divided into two folders depending on their diagnosis (PD for Parkinson's sufferers and NPD for control subjects). Classification error indicates the proportion of incorrectly classified instances within a dataset. It is computed as:

$$Classification\ Error = \frac{Incorrect\ Predictions}{Total\ Predictions} = 1 - Accuracy \tag{6}$$

where Incorrect Predictions is the number of instances where the model predicted the wrong class, and Total Predictions is the total number of instances in the dataset being classified. The model's performance is evaluated using the key performance metrics as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{7}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{8}$$

$$Specificity = \frac{TN}{TN + FP} \tag{9}$$

From the balanced NTUA Parkinson dataset distribution of 20000 images (10000 normal and 10000 PD patients), 60% of images are used for training (6000), 20% for validation (2000), and 20% for testing (2000) sets, ensuring uniform class representation for dependable model development and assessment. The performances of PDCNet are analyzed in terms of accuracy, sensitivity, and specificity. To obtain the performance metrics, the number of images correctly classified by the proposed PDCNet is counted, and a confusion matrix is formed. The proposed system is implemented in MATLAB, and the obtained confusion matrices are shown in Figure 7 for different values of dropout.

It can be seen from Figure 7 that the performance of PDCNet across different dropout ratios shows a consistent improvement in classification accuracy up to a dropout of 0.3. As the dropout increased from 0.1 to 0.3, both true positives and true negatives steadily rose, indicating better detection of PD and healthy cases. At the optimal dropout of 0.3, the model achieved its best results with 9,769 true positives (TP) and 9,885 true negatives (TN), reflecting

the most accurate classification of both classes. However, a further increase to 0.4 led to a slight decline in performance, suggesting that overly strong regularization may reduce model effectiveness. Thus, a dropout of 0.3 offers the most balanced and accurate performance for PDCNet. From the above confusion matrices, the performance metrics are computed are shown in Table 2.

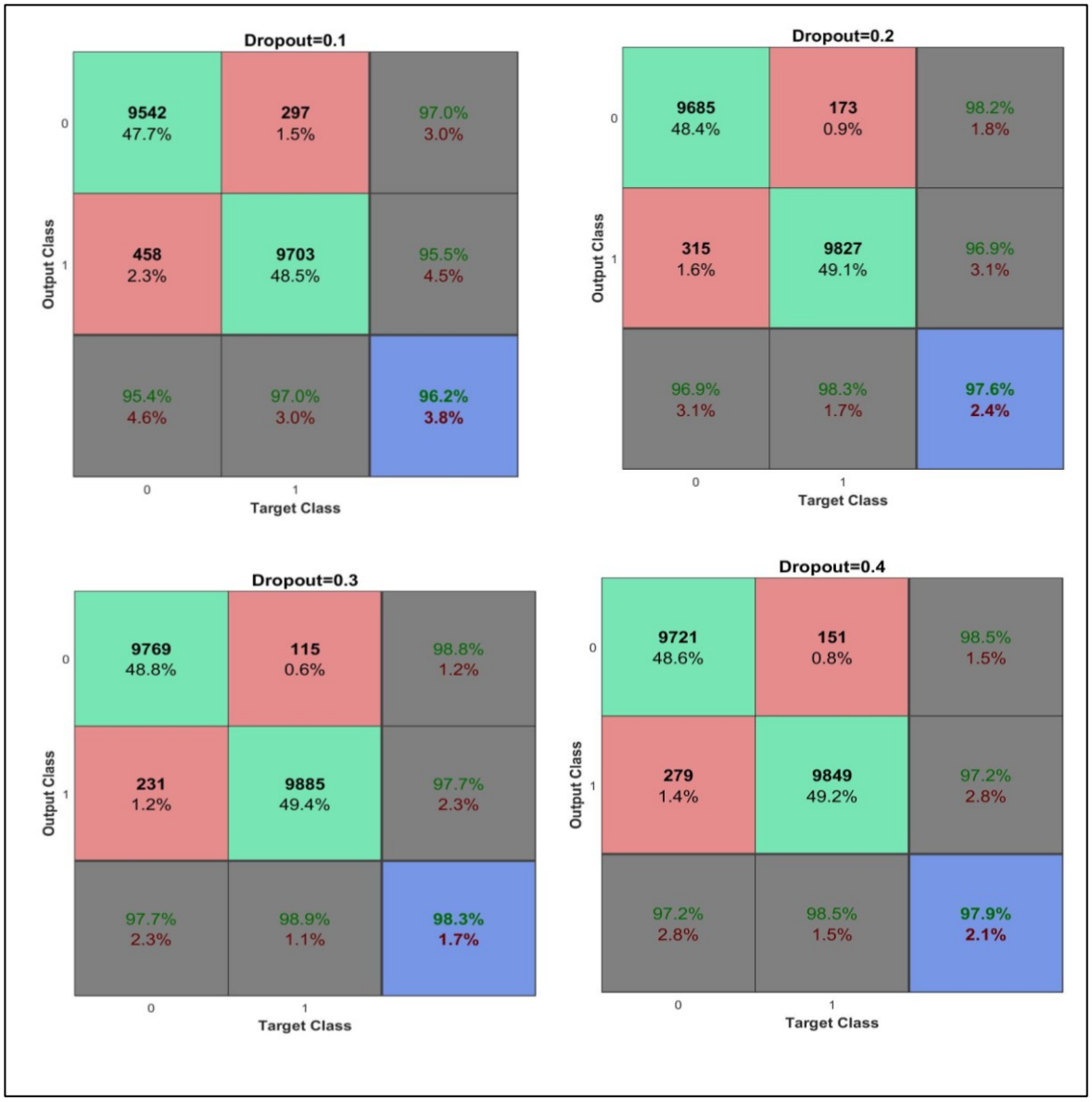

Figure 7. Obtained Confusion Matrices for Different Dropout Ratios for PD Classification

Table 2. Dropout Ratio Performance Comparison for PD Detection

Dropout Rate	TP	FN	FP	TN	Sensitivity (%)	Specificity (%)	Accuracy (%)
0.1	9542	458	9703	297	95.42	97.03	96.23
0.2	9685	315	9827	173	96.85	98.27	97.56
0.3	9769	231	9885	115	97.69	98.85	98.27
0.4	9721	279	9849	151	97.21	98.49	97.85

The comparison in Table 2 demonstrates the impact of varying dropout rates on PDCNet's performance for PD detection. As the dropout ratio increased from 0.1 to 0.3, there was a consistent improvement in the number of true positives and true negatives, as well as in sensitivity, specificity, and overall accuracy. The model achieved optimal performance at a dropout of 0.3, recording 9769 true positives and 9885 true negatives, with peak sensitivity (97.69%), specificity (98.85%), and accuracy (98.27%). This improvement demonstrates the effectiveness of dropout as a regularization technique, which works by randomly deactivating neurons during training to prevent overfitting and enhance generalization. By encouraging the network to learn more robust and redundant features, dropout helps the model to avoid relying too heavily on specific neurons or patterns in the training data. However, at a higher dropout rate of 0.4, performance slightly declines, suggesting that excessive dropout may affect the model's learning capacity. Thus, a dropout rate of 0.3 strikes the best balance, enabling the benefits of regularization without compromising predictive performance. Figure 8 shows the training and validation accuracy and loss throughout epochs, demonstrating the model's enhancement and generalisation efficacy over time.

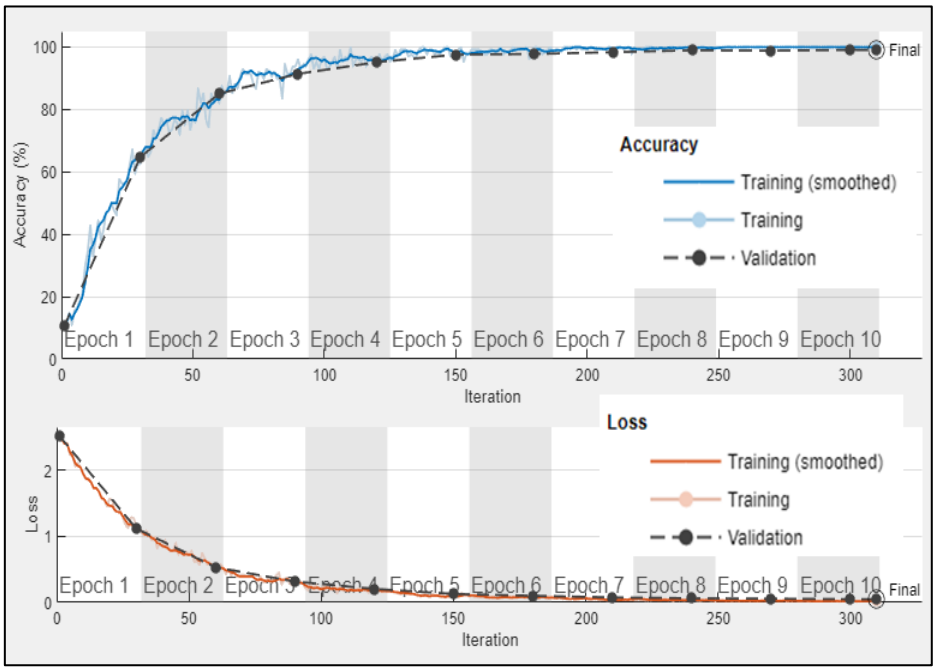

Figure 8. Accuracy and Loss Curve of PDCNet

The above graph depicts the model's accuracy and loss throughout 10 epochs. The variation in training and validation accuracy demonstrates a consistent improvement signifying enhancement of the model. The consistent drop in both losses implies that the model is learning and generalising efficiently, with minimal overfitting. Figure 9 compares several deep learning models for the identification of PD using MRI data.

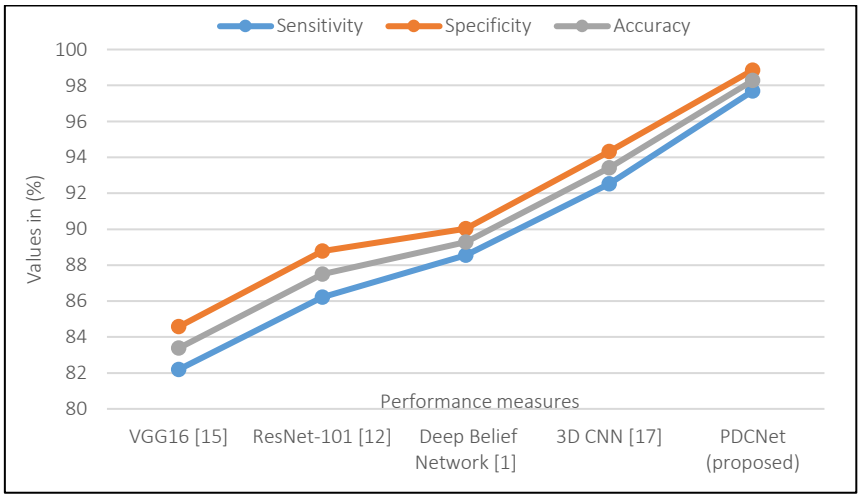

Figure 9. Comparative Analysis of Deep Learning Architectures in PD Classification

The performance comparison in Figure 9 demonstrates that the proposed PDCNet model outperforms all other architectures in accuracy (98.27%), sensitivity (97.69%), and

specificity (98.85%), demonstrating its superior classification ability. 3DCNN follows closely with 93.42% accuracy and 92.52% sensitivity, making it a strong alternative. The VGG16 achieves moderate performance with 83.38% accuracy, 82.19% sensitivity, and a specificity of 84.57%. In contrast, ResNet-121 and deep belief networks show significantly weaker results compared to the proposed PDCNet, suggesting a higher tendency for false negatives. Overall, the PDCNet model exhibits the best balance of high accuracy, sensitivity, and specificity, making it the most effective approach for the given task.

4. Conclusion

The proposed PDCNet-based approach for detecting PD using MRI scans has remarkable efficacy, with an accuracy of 98.27%, sensitivity of 97.69%, and specificity of 98.85%. Utilising the NTUA Parkinson Dataset, the model proficiently detects brain areas impacted by PD, including the substantia nigra and basal ganglia, using advance model such as Grad-CAM for interpretative clarity. The approach improves traditional ML techniques, with deep learning in medical image interpretation. The balanced dataset and the designed PDCNet architecture provide dependable and impartial predictions. The use of dropout methods promotes generalisation, mitigates overfitting, and elevates model performance. The system's capacity to provide interpretable outcomes through Grad-CAM addresses the clinical demands, making it an invaluable asset for healthcare practitioners. Future work includes augmenting the dataset with multi-modal imaging, including clinical data, and implementing the technology in practical environments. This method has the potential to transform early PD diagnosis and enhance patient outcomes by tackling issues such as data privacy and model interpretability. The proposed PDCNet signifies a substantial advancement in using AI for the identification and treatment of neurodegenerative diseases.

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