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A Deep Learning Framework with a Dual-View CNN to Detect Parkinson's disease Using MRI Images

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Abstract: Parkinson's Disease (PD) is a neurodegenerative disordercaused by the lack of dopamine in the brain. Magnetic Resonance Imaging (MRI) is used to assess structural and functional abnormalities in the brain. Although MRI helps to examine these abnormalities, early detection remains difficult due to single–view representation. To overcome this challenge, this paper introduces a dual-view deep learning framework called Dual-View Parkinson's Detector (DVPD) to classify between Parkinson's Disease (PD) and Healthy Controls (HC).The proposed method incorporates two CNNs - a Global brain structure and a focused PD-vulnerable region extracted from MRI slices, which process the global and focal representations separately. The model was trained using data augmentation, the Adam optimizer, and early stopping to minimize overfitting. Unlike prior approaches that rely on heavy and complex architectures, DVPD offers a simple, resource friendly solution. The results demonstrate that the dual-view approach improves subject-level accuracy over baseline single-view CNN models, providing an effective solution for PD classification using MRI.
Keywords: MRI, dual-view, Parkinson's Disease, Light weight Convolutional Neural Network, global brain structure.

1. INTRODUCTION

PD is a progressive neurodegenerative disorder that is linked to the loss of dopaminergic neurons in the substantia nigra, which is responsible for controlling motor functions in the brain [1]. Common symptoms include tremor, rigidity, postural instability and slowness of movement, which worsen gradually over time [2]. Early assessment is crucial due to structural changes that occur before visible symptoms appear [3]. MRI has emerged as a non-invasive technique for capturing brain tissue affected by PD [4]. Some MRI technique is time-consuming and requires expert radiologists to examine. So, there comes a need for automated methods that enable early PD detection [5]. Modern computational techniques, such as Machine Learning (ML) and Deep Learning (DL), are transforming healthcare to a greater extent [6]. ML methods traditionally rely on handcrafted features and classifiers, such as SVM or Random Forest. However, they require manual intervention[7].On the other hand, DL methods automatically learn from patterns extracted from MRI slices[8], [9].Most DL methods employ a single-view architecture.There may be a loss of regional information in single-view analysis [10].To enhance PD characterization, multi-view approaches are necessary for early-stage PD categorization. Recent studies have employed multi-view and multi-region strategies for the detection and classification of various disorders. In particular, dual-view deep CNN (DV-DCNN) is used for matching the detected masses in mammograms [11]. Motivated by this, our paper introduces a dual-view CNN that compares information from both global brain structure and region-focused brain structure to effectively classify PD versus HC. Recently, various studies have been conducted to classify and detect PD. A large number of techniques have been implemented in research works for the detection of PD. Such works, which incorporated diverse ML and DL based methods for detecting PD using MRI data, were discussed.Váradi [12],proposed a clinical review for the evolution of PD symptoms, referring to the motor and non-motor features, and diagnostic challenges.

Sveinbjornsdottir [13], described the features of PD, discussed as progression of the disease, varied treatment strategies, and its complications. Basaia et al. [14], developed a multi-centre 3D CNN for diagnosing PD, thereby effectively differentiating PD from controls using only MRI data. Acikgoz et al. [15], introduced a dense network methodology with an attention mechanism that automatically diagnoses PD from MRI scans. Camacho et al. [16], presented a DL technique that has been trained on a large multi-center database comprised of T1-weighted MRI datasets. Shanthappa et al. [17] proposed a method to detect PD using a DL approach called InceptionV3, which classifies spiral images traced by patients, which was an inexpensive technique to detect PD. Chang et al. [18], explored a multimodal DL method and multi-sequences PET/MR images, accurately differentiating PD from MSA. Srinivasan et al. [19] deployed an ML approach to precisely identify PD from voice signals. Desai et al. [20], developed a model that utilized DL-based classification of 3D MRI images, thereby enhancing the diagnosis of PD, which can aid in treatment at an earlier stage and lead to better patient outcomes. On the whole, existing studies either integrate ML or DL methodologies, focusing mainly on single-view and complex architectures. On the contrary, our methodproposes a dual-view framework and a lightweight architecture, while ensuring robustness at the same time. According to past research, this is the first study (to the best of our knowledge) to propose a dual-view MRI framework, integrating global brain structure and focused information on PD-vulnerable regions for PD detection. Better performance is achieved using a lightweight CNN, compared to other methods that use heavy and complex CNNs. The generalisation gap is reduced by implementing augmentation strategies and standardised preprocessing techniques. The layout of this work is structured as follows: the entire methodology of the proposed method is discussed in Section 2. In Section 3, the results and discussions of the proposed work are presented. Finally, Section 4 addresses conclusions and future work.

2. METHODOLOGY

Figure 1 depicts the workflow of the proposed DVPD model. The MRI images are pre-processed and then trained through global and focal CNN branches. Then, fused together to predict the output.

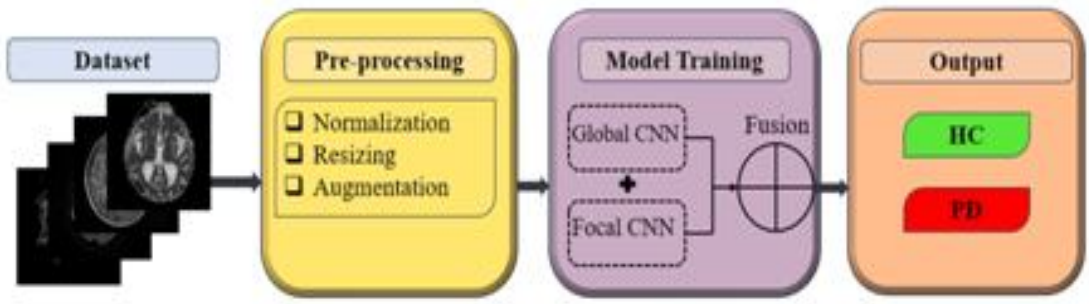

Fig 1. Overview of the proposed DVPD framework

2.1 Dataset

In this study, the encompassed dataset was extracted from a publicly available Parkinson's Brain MRI dataset on Kaggle [21]. Previously, these images were utilized in AI-based PD detection research, in which they were arbitrarily split into training (80%, 337 images), validation (10%, 42 images), and testing (10%, 42 images) subsets to build and validate a convolutional neural network model[22].

2.2 Preprocessing

For our study, the same dataset was implemented, comprising 221 PD and 221 HC images. Images were pre-processed by applying image normalization using min-max scaling.

The full axial slice (global) and the cropped mid-brain region (focal) using fixed bounding-box coordinates were resized to anidentical dimension of 64 x 64 x 1 for both global/focal representation and labels assignment as PD vs HC. The model's generalization has been improved by applying data augmentation to the training set. Relying on the augmentation factor, each image underwent five augmentations. The data is then partitioned into training, validation and test sets in the ratio [80:10:10], conserving class balance in each subset.

The original dataset comprises 582 MRI images, out of which 422 images(221 PD and 221 HC) have been selected to rectify class imbalance. The overall count of images was increased to 2652, containing 1326 PD images & 1326 HC images, and the class balance is maintained.

2.3 Proposed Dual-View CNN Model

This study proposes a dual-view framework for accurate detection of PD using MRI slices. The presented model captures both global and focal brain structures of PD-vulnerable areas, which is illustrated in Figure 2. It is comprised of two parallel CNN branches a global-view CNN and a focal-view CNN. Both branches were designed to extract features from the MRI slices. They contain stacked convolutional blocks, which were followed by pooling layers and activation for feature extraction. The output of each CNN branch is an independent probability score of PD. Finally, the scores of the dual-view images have been fused to form the final prediction.

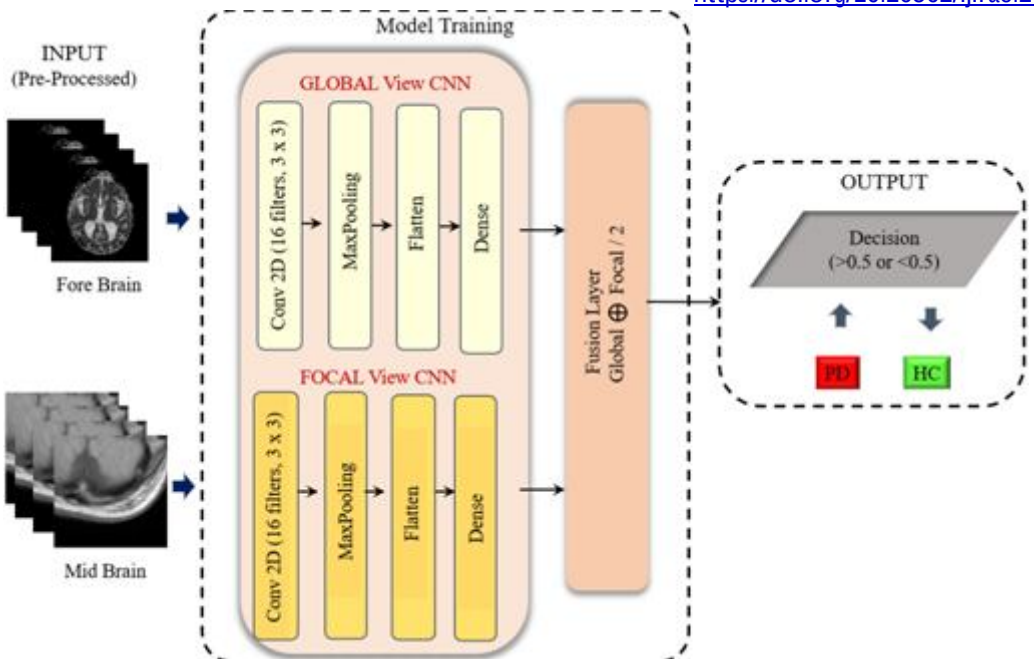

Fig 2. Architecture of the proposed DVPD Model

Global-view CNN (S_g):

The global-view CNN parses the entire MRI slice, capturing the overall brain texture, variations in tissue density, and abnormalities in the structure. Convolutional filters are used to extract spatial patterns, while max-pooling is used to reduce spatial resolution.

$$S_g = f_g(X; \theta_g) \quad (1)$$

Where,

X = input MRI slice

$f_g(.)$ = global CNN mapping

θ_g = learnable parameters of the global CNN

Focal-view CNN (S_f):

The focal-view CNN assessesthe PD-vulnerable region, which has been extracted automatically. This region is identified where PD-linked anomalies were generally observed. This CNN recognizes variations in texture, which may not be visible in the global view.

$$S_f = f_f(X_r; \theta_f) \quad (2)$$

Where,

X_r = cropped region from MRI

$f_f(.)$ = focal CNN mapping

θ_f = learnable parameters of focal CNN

Fusion-Score:

The probability of PD is detected independently in both branches. Then the final prediction is derived by taking the average of both predictions.

$$S_{fusion} = \frac{S_g \oplus S_f}{2} \quad (3)$$

Classification Head:

In the final classification layer$\hat{y}$. The fused score is again predicted and labelled as 0 (HC) or 1 (PD).

$$\hat{y} = \begin{cases} 0, & \text{HC} \\ 1, & \text{PD} \end{cases} \quad (4)$$

Performance Metrics:

The primary evaluation metric, Accuracy, was used to appraise the efficiency of the proposed framework for the global branch and the focal branch. Accuracy represents the proportions of the MRI slices that were precisely categorized as either HC or PD. This is used to clearly distinguish the capability of each branch embedded in the dual-view architecture. The Accuracy was calculated as follows:

$$Acc = \frac{TP_S + TN_S}{TP_S + FP_S + TN_S + FN_S} \quad (5)$$

Where, TP, TN, FP, and FN are the overall true and false positives/negatives.

In our study, an accuracy of 97.44% was achieved in the global-view CNN, and 93.16% was achieved in the focal-view CNN, which demonstrates the optimal nature of both independent branches.

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3. RESULTS AND DISCUSSION

The proposed framework was evaluated on baseline architectures – the Global CNN and Focal CNN, using the same evaluation protocol and preprocessing to ensure a fair comparison. The experimental analysis shows gradual improvements when integrating global and region-focused MRI representations. Table.1 compares the performance of the proposed model with other previous approaches. DVPD architecture works with two separate CNN branches. One branch extract feature from the entire brain while the other branch extracts feature from the PD-vulnerable region. In Figure.3, the prediction of few sample MRI images were displayed. Outputs from both the branches are combined using score-level fusion. This fusion strategy helps the model observe small changes in the brain associated with PD, that results in precise predictions. In Figure.4, accuracy and loss graphs of the global-view CNN is illustrated. In Figure.5, accuracy and loss graphs of the focal-view CNN is visualized. As a result, the presented model achieves high performance across all metrics. With the use of standardized preprocessing and augmentationstrategies, the generalization gap is reduced.

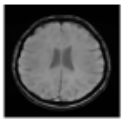
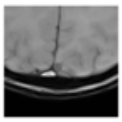
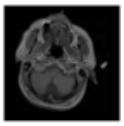
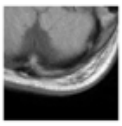
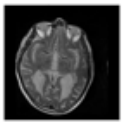
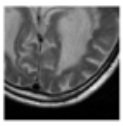
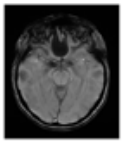
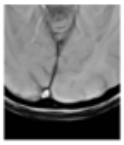
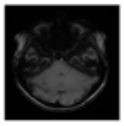
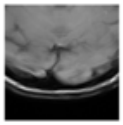
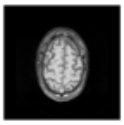
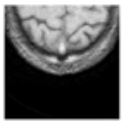
Original MRI Slice	Midbrain Region	Final Score	Detected Output
		0.003	HC
		0.991	PD
		0.998	PD
		0.011	HC
		0.012	HC
		0.999	PD

Table.1 Comparison of proposed DVPD model with existing DL models

Method	Accuracy (%)
AlexNet [23]	88.90
CNN[24]	81.00
CNN[15]	94.44
Proposed DVPD	95.30

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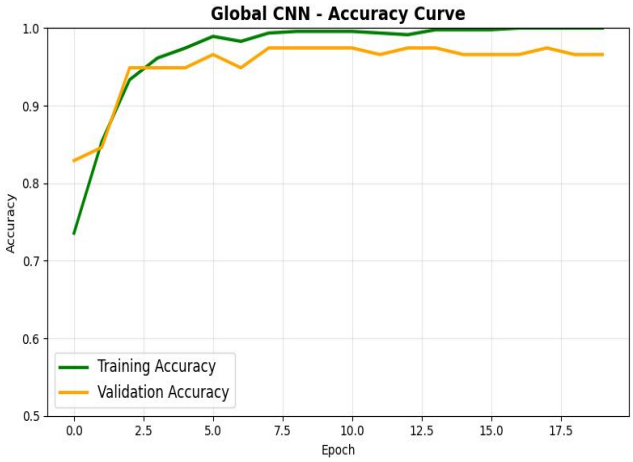


Fig.3 Sample prediction using DVPD Approach

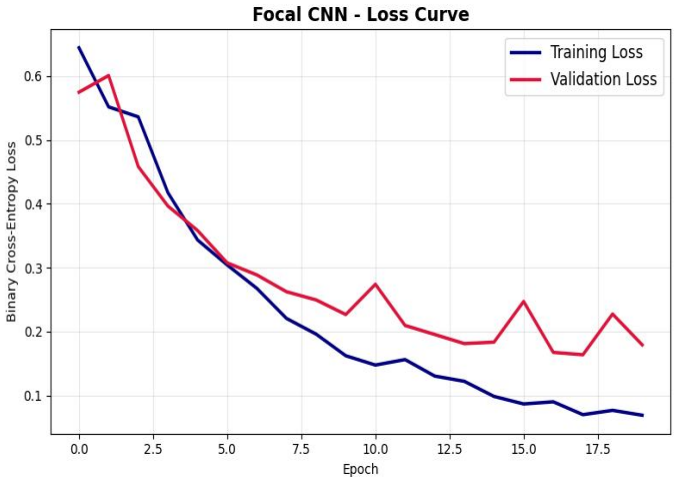
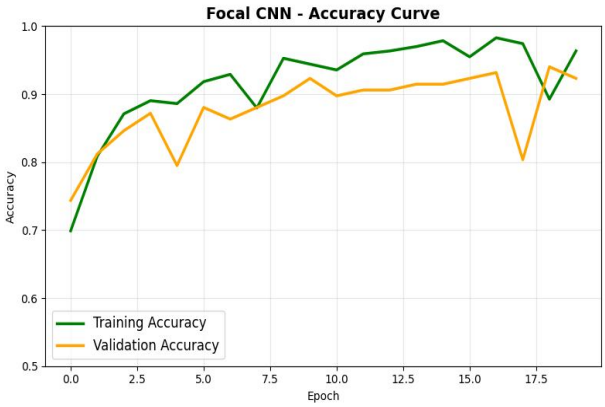


Fig.4 Accuracy and Loss curves of Global CNN



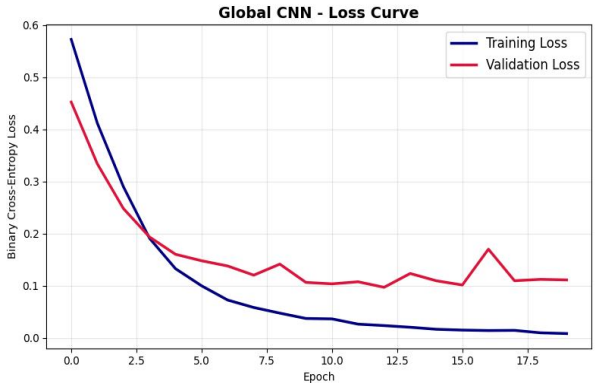


Fig 5 Accuracy and Loss curves of Focal CNN

While comparing with existing previous MRI-based detection methods, our model attains a higher performance despite using lightweight dual-view CNN architecture. Unlike prior a approach that uses complex networks, the proposed model obtains enhanced generalization without increasing complexity.

4. CONCLUSIONS AND FUTURE WORK

This paper presented a Dual-View CNN framework to identify PD from MRI slices. This model uses a Dual-branch CNN architecture, that integrates global and regional structural features. By applying preprocessing and augmentation techniques, this model achieves reliable performance in distinguishing PD and HC. Future work will focus on assessing our proposed model across diverse real-time datasets, thereby enhancing performance and deploying it in clinical environments.

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