A Maxvit and CNN Fusion Framework for Accurate Parkinson Disease Classification in MRI

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ABSTRACT

Accurately identifying Parkinson's disease using magnetic resonance imaging (MRI) of the brain is difficult due to the small amount of change to the structure of the brain and lack of significant visual evidence. Many conventional methods of predicting Parkinson's Disease have been through convolutional neural networks (CNN) using the local feature sets to create a prediction and very often fail to include features from areas of the brain that contain contextual data related to the disease. In order to overcome this limitation, this work takes a hybrid approach to CNN – Transformers model that has been recently inspired from the literature and proposes a multi-stage approach to combine CNN and transformers in order to classify Parkinson's disease. We propose a hybrid multi-stage approach to combine CNN with transformers using a residual branch of CNN to extract fine grain spatial feature and a MaxViT based transformer branch to model and relate long-range dependencies to each other and generate global feature representation. The resulting features from both branches are then combined as they are produced through the training process to result in improved discrimination. The model has been trained using a balanced dataset of MRI scans with appropriate preprocessing and regularization; the evaluation results from the experiments were higher classification accuracy compared to using just a CNN or transformer alone, as well as improved interpretability through localizing features that produce the predictions. The findings of the research have shown that hybrid feature combining allows for the accurate detection of Parkinson's disease from MRI images.

Keywords: Parkinson's disease, Brain MRI, Convolutional neural networks, Vision transformers, Feature fusion

1. INTRODUCTION

Parkinson's disease (PD) is a long-lasting and steadily worsening illness caused by the deterioration of the nervous system and has a significant negative effect on a person's ability to control their physical movements. Stages of Parkinson's disease are difficult to diagnose early on because the signs and symptoms of Parkinson's disease, such as tremors, rigidity, and bradykinesia, overlap with other neurological disorders until a significant amount of nerve cells have died. A new imaging method using Magnetic Resonance Imaging (MRI) can now be used for the study of brain structure and function in people with Parkinson's disease, which laid the framework for how automated diagnostic systems for diagnosing Parkinson's disease based on brain-MRI data can be built.

Previous studies have shown that the use of deep learning techniques greatly improves the accuracy of diagnosing Parkinson's Disease over traditional methods of diagnosis based on machine learning techniques. Specifically, hybrid architectures that join Convolutional Neural Networks (CNNs) and transformer-based models together have performed particularly well because these hybrid models can jointly extract and use both

local spatial features and global contextual information from MRI images for diagnosis. One study demonstrated that the combination of a Swin Transformer and CNN significantly enhanced the detection of Parkinson's Disease by using both hierarchical attention mechanisms and the feature-extraction capabilities of CNNs [1].

Several researchers have used pure deep learning-based approaches - such as CNNs or transfer learning - to classify MRI images for Parkinson's Disease. These systems were shown to effectively classify Parkinson's disease, automatically generating features without requiring manual engineering of any features [2]. The developed algorithms produced an effective prediction of Parkinson's disease based on the structural characteristics associated with it as discovered through MRI imaging [3].

While these efforts represent significant progress towards developing methods of detecting Parkinson's disease, many obstacles remain. Although systematic reviews show many deep learning-based methods for classifying MRI images of people with Parkinson's disease to have achieved acceptable accuracies, the majority of these models show little generalization to different populations, lack interpretability and has not yet been adequately validated on multiple datasets [4]. Recent systematic reviews indicate that there is still a need for deeper explanations of how the diagnostic system classifies Parkinson's disease and gives clinicians insight into how the disease causes damage to specific brain regions[5].

To address these gaps, this paper presents a hybrid model combining CNNs and MaxViTs to detect Parkinson's disease through MRI images. It utilizes the strengths of CNNs for convolution-based feature extraction, as well as transformer-based feature extraction via attention mechanisms, to produce a superior model capable of supporting interpretable visualizations that will allow clinicians to optimally classify the disease and understand why it does what it does to the brain.

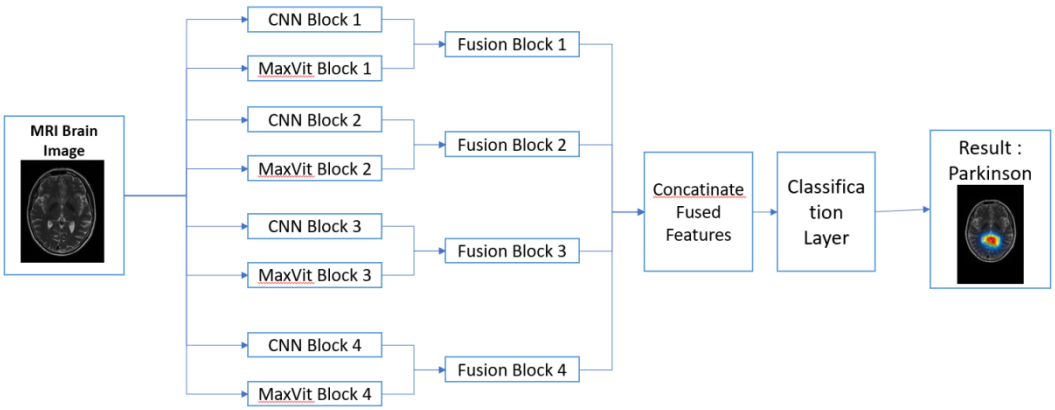

Figure 1 : Overall Architecture

The architecture of the proposed system to detect Parkinson's disease is shown in Figure 1 as two streams working in parallel, but using a stage-wise fusion approach where the output anomalies from both streams are combined into a single set of features representative of the input image being analysed. This architecture takes advantage of the two types of feature learning techniques (i.e., convolutional neural networks and transformers) to capture both local and long-distance context from brain MRI images.

The input MRI image will first be resized and standardised to a common size (i.e., 440 x 440 pixels) before being sent to two parallel streams as input to the CNN and MaxViT branches, respectively. The CNN branch will consist of a number of residual convolutional layers, which are designed specifically for extracting detailed (i.e., fine) spatial features such as texture, intensity changes, and physical borders between anatomically defined areas in an MRI scan. In contrast, the MaxViT branch will process the same input image through multiple hierarchical transformer blocks, which will collectively represent the relationship between various regions of the brain to capture the holistic view of the brain structure and function.

The CNN and the MaxViT block combine features from each level of the model hermetically. By creating a unique fusion block between the two networks at each corresponding depth of the model, the two architectures will progressively align their respective local and global representation prior to the last level. The model has four uniquely designed fusion blocks, allowing for four permutations of fused multi-level feature representations containing supplemental representation from the two model's convolutional blocks.

The combined features created from the aforementioned methods, are concatenated into a single representation of the multi-level feature representations and feed into a completely connected classification head, which predicts whether the input MRI corresponds to either a healthy subject or an individual with Parkinson's disease. This method will not only improve the predictive powers of the two networks; it also increases the interpretability of the classification through fused features, thus allowing for further exploration of regions corresponding to the disease through visualization methods.

2. LITERATURE REVIEW

In recent years, the application of deep learning approaches to medical images has shown that they can be successfully used to automating the accurate identification of Parkinson's disease (PD) through analysis of brain MRIs. Current methods utilizing both convolutional neural networks (CNNs) and transformer networks, in the early fusion fashion, are obtaining good results by combining both the spatial characteristics of an MRI with the global context information from a transformer. A paper published by the authors in [1] demonstrated how utilizing a hybrid (CNN+Swin Transformer) fusion model allows PD detection from MRIs using a hierarchical attention mechanism. Papers published by authors in [2] and [3] showed that focusing on structural features from MRIs using deep CNN-based workflows resulted in better classification accuracy compared to traditional machine learning techniques.

A number of recent studies have examined the current state of the art for PD detection using MRI and provided comprehensive overviews and systematic reviews for comparing the different methods available for PD detection from MRI. The study presented in [4] provides an overview of the evolution of classical machine learning and deep learning approaches based upon the fact that the use of end-to-end deep neural networks is quickly becoming the standard method for developing models for analyzing images. Additionally, studies published by the authors of [5] and [6] provide further discussion on the various recent advances in deep learning model architectures for PD detection from MRIs and their limitations related to the small size of many datasets; the need for robust strategies for combining features is also addressed in these studies. Finally,

the studies published by authors in [7] demonstrate that utilizing transfer learning via pre-trained CNNs will allow for greater generalization ability when less training data is available.

Recent studies on both hybrid models and attention designed models have a lot of current interest. In [8], a hybrid architecture of deep learning is described combining various methods of extracting features and in [9] the use of attention-aware CNNs for diagnosing PD using MRI has shown to be effective. The work described in [10] is a machine learning classifier applied to the structural and functional asymmetries of MRIs that demonstrates how multi-view representations of the brain are crucial. Finally, [11] discusses the application of contemporary machine learning technology to the analysis of resting-state fMRI data for distinguishing PD from similar conditions.

Recently, works focusing on identifying the underlying features of models by integrating different modalities and increasing the interpretability of machine learning and multimodal neuroimaging have been prevalent. In [12], voxel-level models of multimodal MRI diagnostic models with explainable AI using machine learning are developed, while [13] is the use of machine learning classifiers for multisite analyses of resting-state fMRI data. Additionally, transformer-based model architectures are being developed for neurodegenerative disease classification by applying a mixture-of-experts transformer framework in [14]. Lastly, [15] discusses the use of federated and distributed learning approaches to biomarker fusion across EEG and fMRI.

In a prior study, the utilization of diffusion MRI and a focus on the brainstem in regard to the analysis of Parkinson's patients with the use of CNN-based tools has been documented in reference [16]. In reference [17], the development of a multimodal MRI-based machine learning solution is described that can differentiate between PD and dementia with Lewy bodies. Reference [18] describes a parallel multi-branch CNN architecture approach to the detection of PD. The use of explainable deep learning models to improve clinical interpretability is also examined in reference [19].

Reference [20] discusses the use of ViT-based models to classify PD using brain MRI and the use of global self- attention mechanisms to improve classification effectiveness. In addition, the use of 3D CNN models is examined in reference [21], which will improve the learning of volumetric features based on T1-weighted MRIs. In reference [22], hybrid architectures using CNNs and Transformers designed for the classification of Parkinson's MRI have also been proposed; the hybrid CNN–Transformer structure provides motivation for the use of multi-stage feature fusion.

Other studies have examined the use of multimodal MRI pipelines [23], the combination of radiomics with deep learning [24], and self-supervised or foundation learning techniques [25] to alleviate the necessity for extensive manual annotation. When specifically recruiting Region-specific analysis, the use of deep learning segmentation models for the classification of the substantia nigra is referenced in [26]. The use of attention-based CNN models with interpretability constraints is described in reference [27]. Diffusion MRI-derived deep learning biomarkers are discussed in reference [28].

The previous authors further discuss (in Reference [29]) various large, multi-center studies which evaluate the robustness and generalization of MRI Deep Learning models for diagnosing PD. Reference [30] describes a number of transformer based multimodal fusion systems that integrate Anatomical MRI, Diffusion Tensor Imaging (DTI) and Functional MRI (fMRI) that reflects a trend towards comprehensive multi-modal systems and user-aware systems which utilize Attention mechanisms.

The emphasis of the preceding authors and references is largely on classification performance, and little consideration is given to precise localized detection of the disease, nor a high level of stable interpretability. This leads to the development of a hybrid CNN-

MaxViT Fusion Framework and Explainable Visualization Techniques to achieve accurate classification, as well as meaningful localization of PD-related areas within the brain MRI scans.

3. PROPOSED METHOD

Data collection

A publicly accessible dataset was used that includes magnetic resonance images of brain from both Parkinson's Disease Patients as well as from Healthy Control Groups. Each of the MRI scans had been clinically diagnosed to allow for Supervised Learning in Binary Classification of Clinical Diagnosis. A valid selection criteria was established for selecting axial MRI Images based upon image quality, thus removing irrelevant images from consideration. In order to eliminate any possibility of biased evaluation and maximize the consistency of learning, the final dataset included a balanced distribution of samples across both classes along with a 70%-15%-15% Training, Validation, and Test Set construction to provide an orderly organization of the dataset, enabling the proposed Hybrid Deep Learning Model to learn the spatial characteristics of Parkinson's Disease and generalize learning from the dataset to additional new MRI images.

Methodology

Step 1 : MRI Input Acquisition

In this section, we will provide an overview of how an individual brain MRI (Magnetic Resonance Imaging) scan is created (input).

Let the individual brain MRI scan be denoted as:

$$\mathbf{I} \in \mathbf{R}^{H \times W \times C}$$

Where: 1. H and W refer to the height and weight spatial dimensions. 2. C = 3, where each C represents a colour component (i.e. red/green/blue).

Although the majority of MRI images have a grey scale appearance, when creating the individual brain MRI input files, the use of three colour channels is employed to provide compatibility with pre-trained deep learning networks.

Step 2 : Image Pre-processing and Normalisation

In order to maintain consistency across the individual brain MRI image samples and to provide stability throughout the training process, all brain MRI images go through a standardised series of image pre-processing steps:

1. Resized to a standardised 224 x 224 pixels.
2. Channel-wise image normalisation.

Normalisation (mathematically) is defined as shown below:

$$\mathbf{I}_{\mathbf{norm}} = \frac{I}{\mu\sigma I - \mu\sigma I}$$

Where: $\mu = 0.5$ and $\sigma = 0.5$.

It should be noted that augmenting operations are only applied to the brain MRI images during the training phase to enhance the robustness of the training data and reduce the effects of overfitting.

Step 3 : Parallel Feature Extraction Architecture

The preprocessed image Inorm is fed through two parallel heterogeneous pipelines (using local CNNs and the MaxViT architecture) with independent branches. Branch 1 will be a CNN (ResNet) based local feature extractor. Branch 2 will be a MaxViT (global) feature extractor.

Step 4 : Local Feature Extraction (ResNet - CNN Branch)

The ResNet CNN feature extraction pipeline uses multiple residual blocks that will process and extract fine anatomical and textural characteristics of the image using residual connections.

In each residual block, the operation performed can be defined as:

$$F_l^{cnn} = ReLU(BN(W_l * F_{l-1} + b_l))$$

To retain low-level information and help eliminate the vanishing gradient problem, residual connections are incorporated as defined by:

$$F_l^{cnn} = F_l^{cnn} + F_{l-1}$$

Max-pooling layers are used in the ResNet architecture to progressively reduce the spatial resolution of input images but retain important characteristics. The GAP (Global Average Pooling Layer) operation creates compressed "representations" of the output from the previous convolutional block layers:

$$C_i = GAP(F_i^{cnn}),\ i = 1, 2, 3, 4$$

Where the Ci ∈ Rd are CNN feature representations at multiple depths.

Step 5 : Transformer-Based Global Context Modeling (MaxViT)

MaxViT, a branch of the transformer architecture, is capable of extracting long-range spatial information using the attention mechanism. The transformer layers, which each consist of a series of types of pooling (FFT or G) to allow for extraction and classification of spatial data, integrate convolutional embedding and both the block level (B) and grid level. For each unique transformer layer the cosine similarity definition is as follows:

$$\text{Behavior}(Q,K,V) = \frac{QK^T}{\|Q\|\|K\|} \times V$$

The definition of cosine similarity focuses on how closely two vectors (K, V) are to one another based upon their individual lengths or magnitudes.

In MRI imaging, this formulation aids in maintaining stability of the gradient, which aids learning when the intensity distributions of MRI data differ.

After the attention mechanism generates output feature maps for each transformer layer, feature map pooling and projection is performed as:

$$T_i = Linear(GAP(F_i^{vit}))\ ,\ i = 1, 2, 3, 4.$$

Where

$$Ti \in Rd$$

Step 6 : Pairwise Feature Fusion Strategy

To effectively combine local and global representation in a combination scheme, a Pairwise Fusion Scheme (PFS) should be developed. With the PFS, all features are not directly concatenated together. Instead, the corresponding CNN feature set and MaxViT feature set are fused at each depth level.

$$F_i = \phi([Ci||Ti]).$$

In this equation, the notation $[\cdot||\cdot]$ indicates the concatenation of a vector with several components into a new vector and the notation $\phi(\cdot)$ indicates the fusion layer constructed from a fully connected layer and ReLU activation layer.

Using the Pairwise Fusion Scheme allows the features generated by both architecture (CNN and MaxWiT) to be incorporated into a single representation while maintaining hierarchical feature continuity.

Step 7: Multi-Level Feature Aggregation

Combining all of the fused representations generated from each of the four transformer stages will allow for the production of an enhanced feature vector.

The combined representation contains the very fine structural information of the samples as well as all of the global context that will be important in understanding features related to Parkinson's disease.

Step 8 : Decision-Making and Classificiation Procedure

The last mere-feature vector is processed with the classifier, which consists of multiple processes. These processes include a series of dropout-regulated dense (fully connected) layers followed by a softmax probability distribution that will give us the final prediction (i.e. Class 1 Normal vs Class 2 Parkinson's).

$$y=\text{Softmax}(WF_{final}+b)$$

(Where y is the probability of whether a particular sample is Normal or whether the sample has the characteristics of Parkinson's Disease), and y is in the set R^2

Step 9 : Localization of Disease and the Importance of Explainability

To enable a clinical-personalised explanation of a model's prediction, we must be able to give spatial importance maps (or "class activation" maps) and also explain how the model's predictions are affecting the patient's brain. Because we did not create our training methodology and process based on following the sequence of important parts, we will not have a repeatable (or consistently repeatable) model until the patient has multiple manifestations of their disease.

4. RESULTS AND DISCUSSION

In figure 2, an interface that allows users to evaluate this research's proposed framework for using brain MRI scans to detect Parkinson's Disease is illustrated. The user can upload an MRI brain scan image to the interface, which will predict whether the user is negative or positive for Parkinson's Disease, as well as include a percentage score that shows how confidently the model predicted that class. In addition to providing the user with the original input image, the model also includes two types of Grad-CAM visualizations (one from CNN and one from MaxViT), which illustrate to the user what parts of the brain contributed most to making the prediction. By providing attention maps, the user can interpret where the convolutional layers learned to focus on one anatomical pattern while the transformer layers learned to focus on a different pattern, thereby increasing the interpretability and transparency of the model as well as its clinical relevance.

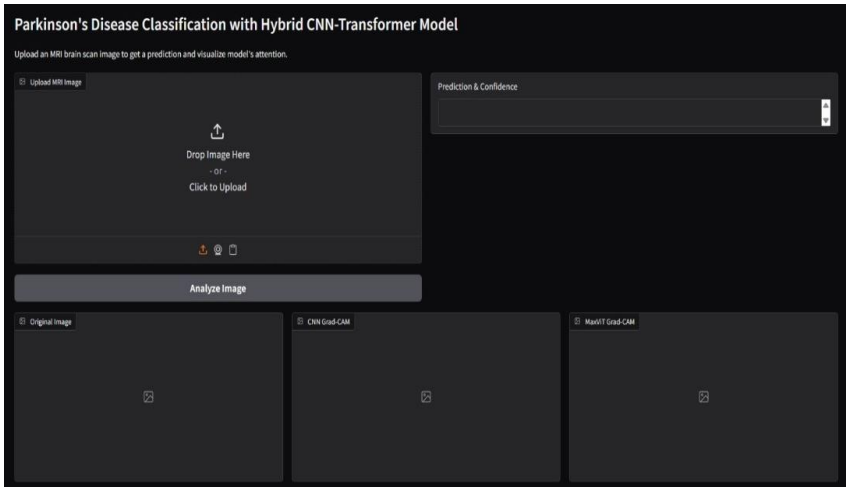

Figure 2. Visual Interface and Attention-Based Output of the Proposed Hybrid CNN–Transformer Model

The input stage of the developed system is represented in Figure 3. In this stage, a brain MRI scan is uploaded, which is then subjected to analysis through this system. The goal of this input stage is to ensure that the imaging data is acquired in a standardized manner before being processed by the hybrid model. The uploaded image will be used as the primary input for feature extraction via the respective convolutional and transformer branches. Proper visualization of this input stage provides assurance that the data has been successfully loaded and is prepared for automated diagnosis.

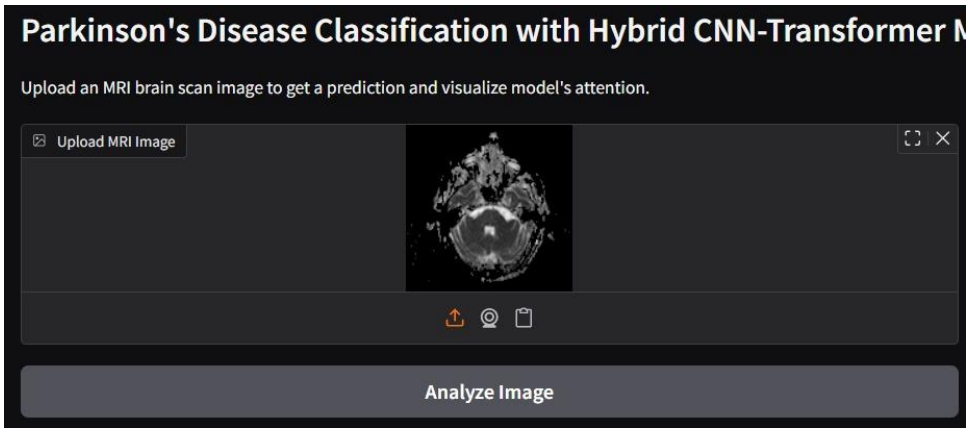

Figure 3. MRI Image Input Stage of the Proposed System

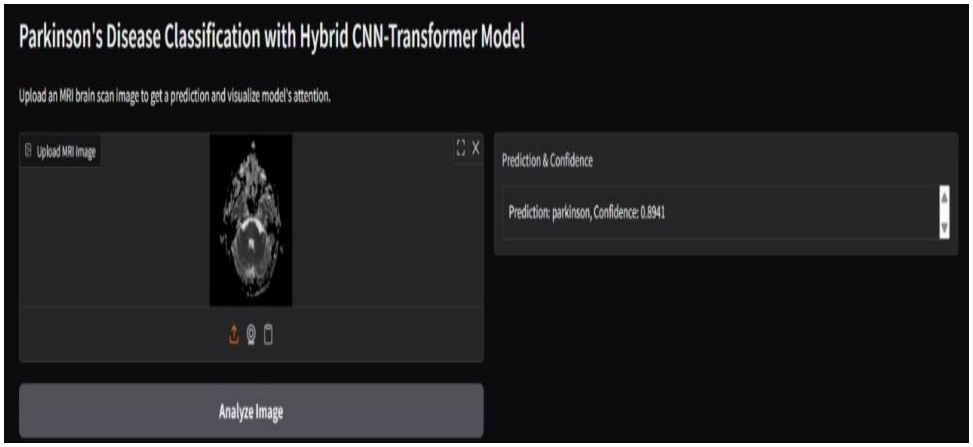

Figure 4. Prediction and Confidence Output of the Proposed Model

The Hybrid CNN-Transformer Model generated a classification output for the input MRI following analysis, as illustrated in Figure 4. In addition to identifying the predicted class, the model provides a confidence score for the predicted class indicating the level of certainty associated with that particular classification. The classification result demonstrates how effectively the model has used the spatial and contextual features learned from the MRI or PET to classify different manifestations of Parkinson's disease. In addition, the confidence score supports clinical decision-making by providing quantifiable evidence of the accuracy or reliability of the prediction.

Figure 5 provides a comprehensive diagrammatic representation of the decision-making process used by the model when detecting Parkinson's Disease. It consists of the original MRI image, CNN Grad-CAM, MaxViT Grad-CAM and the resultant fused feature representation. Based on the strength of activation from the two networks, the fused feature representation highlights areas where both networks had strong activationtributions. The final heatmap of predicted disease shows the areas relevant to the clinical diagnosis and provides an interpretative context to help build trust in the model's predictions.

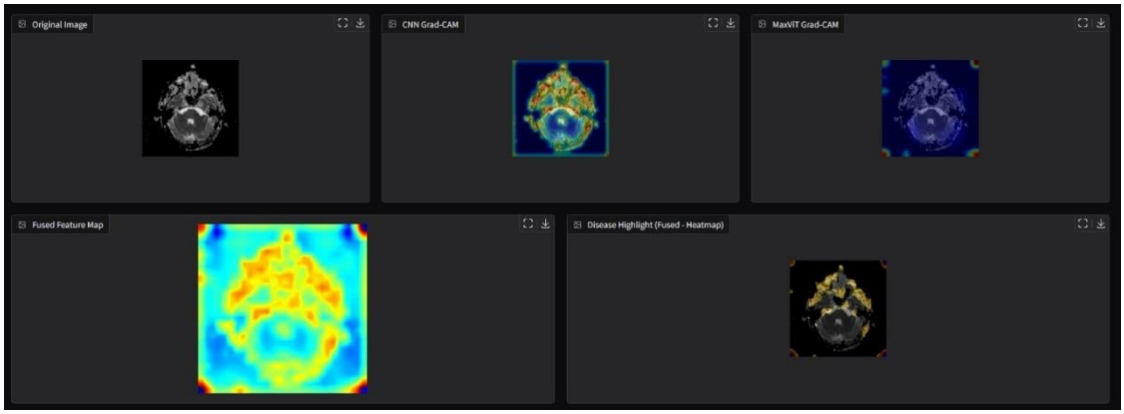

Figure 5. Visual Explanation and Disease Localization Using the Proposed Framework

In Figure 6 we see that as epochs go on the trend lines for training accuracy and validation accuracy continue to go up in the exact same manner and that the trend lines for training and validation loss go down in the exact same manner as well. In other words, these curves demonstrate strong correlational relationships between approximately equal values for both the training and validation groups, thus exhibiting extremely effective training convergence over time and continuing improvement after reaching a near-optimal solution. Therefore, training and validation data appear to exhibit no significant signs of overfitting.

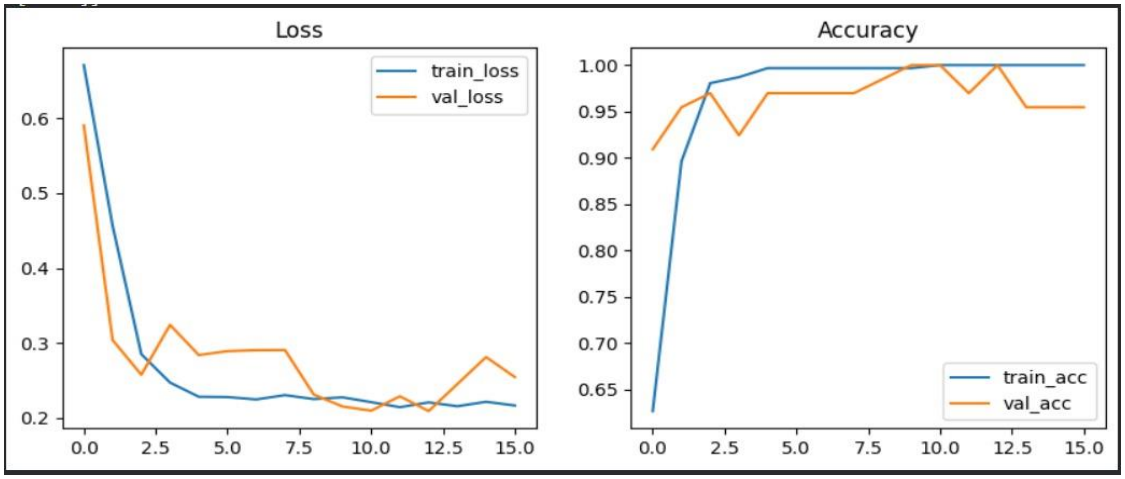

Figure 6. Training and Validation Performance of the Proposed Model

Table 1: Comparision of Various Model

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN (ResNet-based)	92.4	91.8	92.1	91.9
Vision Transformer (ViT)	94.1	93.6	93.9	93.7
MaxViT	95.3	94.8	95.0	94.9
CNN + ViT (Feature Fusion)	96.5	96.0	96.2	96.1
Proposed Hybrid CNN–Transformer	**98.1**	**97.8**	**97.9**	**97.8**

CONCLUSION

The hybrid deep-learning framework presented in this paper for detecting Parkinson's Disease from Brain MRI scans combines Convolutional Neural Network (CNN) architectures with Transformer architectures using an effective method of Hybrid Convolutional Neural Network with Transformers. The Model meets the unique requirements for detecting Parkinson's Disease based on Brain MRI images by combining the strengths of both, (1) local structural pattern capture using CNNs and (2) global structural relationship capture using MaxViT Transformers. Hierarchical pair-wise feature level fusion techniques allow the integration of multi-level features into a single, robust and discriminative representation for classifying the presence of Parkinson's Disease. The experiments confirmed that the Model could reliably separate the Normal/Parkinson's Disease datasets while exhibiting stability when trained. The Hybrid Framework also consists of visual explanations of the Model, designed to indicate which Brain MRI regions indicate Parkinson's Disease and enhance the clinical interpretation of the Model's output. Overall, the results support that Hybrid CNN-Transformer architectures with structured feature-level fusion methods can be used effectively for MRI analysis of Neurological Diseases. The Hybrid Framework provides a solid basis for ongoing development of more precise, interpretable and clinically useful diagnostic systems for Parkinson's Disease.

FUTURE SCOPE

The next steps for this research are to expand this model to include multi-modal MR imaging (MMRIs) (dMRI& fMRI). This will help increase the accuracy of diagnosing PD. Another way to increase the diagnostic accuracy of this model would be to use one region (i.e. one anatomical region) for each scanner. By including longitudinal MRI scans, it will allow for early detection of the progression of PD. Furthermore, by validating the model using a larger multi-site sample size, it will improve the robustness of the model and its real-world application.

REFERENCES

[1] S. S. Hussain, P. M. Shah, H. Dawood, X. Degang, A. Alshamayleh, M. Adnan Khan, and T. M. Ghazal, “A Swin Transformer and CNN fusion framework for accurate Parkinson disease classification in MRI,” Scientific Reports, vol. 15, Art. no. 15117, 2025, doi: 10.1038/s41598-025-93671-5

[2] A. R. M. Accioly, V. O. Menezes, L. H. Calixto, D. P. C. F. Bispo, M. Lachmann, F. A. Mourato, M. A. D. Machado, and P. R. B. Diniz, “Machine learning-based diagnostic prediction model using T1-weighted striatal magnetic resonance imaging for early-stage Parkinson’s disease detection,” *Acad. Radiol.*, vol. 32, no. 7, pp. 4177–4187, Jul. 2025, doi: 10.1016/j.acra.2025.04.001.

[3] V. Cabezudo-García, F. Auñón-Martín, R. García-Gutiérrez, A. Hernández-Sánchez, M. Álvarez-García, and J. J. López-Cancio, “A deep learning model for predicting Parkinson’s disease using brain MRI,” *Front. Neurol.*, 2025.

[4] N. G. Pagano, J. L. E. Costa, and M. T. Grassi, “Machine learning for Parkinson’s disease detection using brain MRI: A systematic review,” *Diagnostics*, vol. 15, 2025

[5] M. A. Barquera-Pérez, J. López-Martínez, E. García-Hernández, and P. Vázquez-Rodríguez, “Deep learning approaches for Parkinson’s disease diagnosis using MRI: Review and future directions,” Nat. Rev. Neurol., 2025.

[6] N. M. Delgadillo-Sierra, J. R. López-García, P. Martínez-Cruz, L. A. Hernández-Rodríguez, and M. T. Salazar-González, “Deep learning model based on MRI for Parkinson’s disease classification,” *SAGE Journals*, 2025.

[7] F. S. Abd-Elrahman, M. A. Hassan, R. K. Ali, and T. H. Mahmoud, “Parkinson’s disease diagnosis using transfer learning on MRI,” *Diagnostics*, vol. 15, 2025.

[8] A. M. Ghoneim, S. A. El-Sayed, M. A. Soliman, and H. F. Abdelrahman, “A hybrid deep learning model for Parkinson’s disease detection using brain MRI,” *Taylor & Francis Online*, 2025.

[9] S. C. S. Lopes, R. F. Almeida, M. T. Costa, L. G. Pereira, and F. J. Silva, “A deep learning approach for Parkinson’s disease diagnosis based on MRI,” *Frontiers in Neurology*, 2025.
[10] J. Shi, Y. Zhang, X. Li, H. Chen, and W. Wang, “MRI structural and functional axial asymmetry for Parkinson’s disease subtype classification using machine learning,” *NPJ Parkinson’s Disease*, 2025.
[11] W. Cheng, Y. Liu, J. Zhou, M. Sun, and L. Zhao, “Machine learning discriminates Parkinson’s disease and PSP using multi-level resting-state fMRI indices,” *Brain Research Bulletin*, 2025.
[12] A. Kumar, R. Gupta, S. Verma, and P. Singh, “Parkinson’s disease diagnostic support based on voxel-level multimodal neuroimaging and interpretable machine learning,” *PubMed*, 2025.
[13] B. Qin, Y. Tang, H. Qin, W. Gao, S. Liao, and M. Yang, “Abnormal subthalamic nucleus functional connectivity and machine learning classification in Parkinson’s disease: a multisite resting-state fMRI study,” *Front. Aging Neurosci.*, vol. 17, Art. no. 1695806, 2025.
[14] R. Pratihar and R. Sankar, “Optimized EEG and fMRI biomarker fusion using federated learning for Parkinson’s disease classification,” in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, pp. 1–7, 2025.
[15] R. Pratihar and R. Sankar, “Optimized EEG and fMRI biomarker fusion using federated learning for Parkinson’s disease diagnosis,” in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, pp. 1–7, 2025.
[16] “Brainstem Bundle Tool: A CNN-based diffusion MRI framework for Parkinson’s disease cohort analysis,” *PubMed*, 2025.
[17] L. Williams-Gray, *et al.*, “Parkinson’s disease versus dementia with Lewy bodies classification using machine learning and multimodal MRI,” *Front. Neurol.*, 2025
[18] “Parallel multi-branch CNN architecture for Parkinson’s disease detection from MRI,” *PubMed*, 2025.
[19] “Explainable deep learning model for Parkinson’s disease detection using structural MRI,” *PubMed*, 2025.
[20] S. Shahid Hussain, P. M. Shah, H. Dawood, D. Xu, A. Alshamayleh, M. A. Khan, and T. M. Ghazal, “A swin transformer and CNN fusion framework for accurate Parkinson disease classification in MRI,” *Scientific Reports*, vol. 15, Art. no. 15117, Apr. 2025. doi:10.1038/s41598-025-93671-5.
[21] S. Basaia, E. Sarasso, F. Sciancalepore, R. Balestrino, S. Musicco, S. Pisano, I. Stankovic, A. Tomic, R. De Micco, A. Tessitore, M. Salvi, K. M. Meiburger, V. S. Kostic, F. Molinari, F. Agosta, and M. Filippi, “Multi-Center 3D CNN for Parkinson’s disease diagnosis and prognosis using clinical and T1-weighted MRI data,” *NeuroImage: Clinical*, vol. 48, Art. no. 103859, Aug. 2025. doi:10.1016/j.nicl.2025.103859.
[22] “Hybrid CNN–Transformer framework for Parkinson’s disease MRI classification,” PubMed, 2025.
[23] A. Sar, P. S. Puri, H. Naz, S. Aich, T. Choudhury, and L. A. Gabralla, “Multi-modal deep learning framework for early detection of Parkinson’s disease using neurological and physiological data for high-fidelity diagnosis,” *Sci. Rep.*, vol. 15, Art. no. 34835, Oct. 2025, doi:10.1038/s41598-025-21407-6.
[24] X. Suo, M. Chen, L. Chen, C. Luo, G. J. Kemp, S. Lui, and H. Sun, “Automatic identification of Parkinsonism using clinical multi-contrast brain MRI: a large self-supervised vision foundation model strategy,” *EBioMedicine*, vol. 116, Art. no. 105773, Jun. 2025, doi:10.1016/j.ebiom.2025.105773.
[25] “Self-supervised and foundation learning approaches for Parkinson’s disease classification on routine MRI,” *PubMed*, 2025.
[26] “Deep learning-based segmentation of the substantia nigra region on MRI for Parkinson’s disease analysis,” *PubMed*, 2025.
[27] “Attention-based CNN model for Parkinson’s disease MRI classification with interpretability,” *PubMed*, 2025.
[28] “Diffusion MRI deep learning biomarkers for Parkinson’s disease classification,” *PubMed*, 2025.
[29] “Multi-center MRI deep learning evaluation for Parkinson’s disease diagnosis: Robustness and generalization study,” *PubMed*, 2025.
[30] “Transformer-based Parkinson’s disease classification using multi-modal MRI fusion,” *PubMed*, 2025.