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Innovative Deep Learning Approach for Parkinson's Disease Prediction: Leveraging Convolutional Neural Networks for Early Detection

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Abstract

INTRODUCTION: Parkinson's disease (PD) is a progressive neurodegenerative disorder affecting movement control, highlighting the importance of timely detection and intervention to improve patient quality of life. However, accurate diagnosis remains challenging due to its similarity with other neurological conditions, leading to a 25% rate of inaccurate manual diagnoses. Convolutional Neural Networks (CNNs) offer a promising solution for medical image classification and analysis, capable of learning complex patterns in images. In this study, we introduce an innovative automated diagnostic model using CNN that gives an appropriate output about if the person is diagnosed with PD or not.
OBJECTIVES: The study aims to develop an automated diagnostic model using CNNs to accurately diagnose PD. By leveraging the Parkinson Progression Markers Initiative (PPMI) dataset, which provides benchmarked MRI images of PD and healthy controls, the model seeks to differentiate between PD and non-PD cases.
METHODS: A Convolutional Neural Network (CNN) is a deep learning algorithm that is suitable for medical image classification and analysis as they are able to learn complex patterns in images and identify the hidden patterns and trend of data. We have used VGG16 and ResNet50 pretrained CNN models to achieve high accuracy and prediction.
RESULTS: These models collectively achieved an outstanding accuracy rate of 97%. To validate our model performance, we test our model by applying various algorithms and activation functions such as EfficientNetB0, EfficientNetB1 and softmax, sigmoid, and ReLu respectively.
CONCLUSION: This research introduces an innovative framework for the early detection of Parkinson's disease using convolutional neural networks. Our system demonstrates remarkable capability to identify subtle patterns indicative of PD in its early stages.

Keywords: Parkinson Disease, Healthy Control, Convolutional Neural Network, MRI, Deep Learning.

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1. Introduction

Parkinson's disease (PD) is a complex and non-curable neurological condition that impacts millions of individuals globally. It was first medically described as a neurological syndrome in an essay, "An Essay on the Shaking Palsy" by Dr. James Parkinson in 1817. The disease occurs in the part of the brain known as substantia nigra, which is responsible for dopamine release. Dopamine is a neurotransmitter that works as the medium in establishing communication between brain cells and contributes within the movement and co-ordination of the body. Parkinson's disease is most commonly diagnosed in older adults above the age of 60 years, though it can also occur earlier in life. Symptoms of PD are trembling, posture stiffness, uncontrolled movements and coordination; patients may also face sleeping problems, difficulty in thinking and memorization.

Although the disease still has no cure, there are treatments and therapies for improving the quality life of patients. Treatment includes medication, physical therapy, speech therapy, occupational therapy and surgical intervention, including deep brain stimulation, which can be beneficial in managing the condition. The symptoms and progress rate of PD can be different for individuals. Early signs of the disease appear slowly and subtly. Medical diagnosis of PD is performed by using Medical History, Clinical Examination, Neurological Assessment and Response to Medication, which includes many tests and assessments. The difficulty in achieving accurate diagnoses of PD arises from its resemblance to other diseases, which results in a 25% rate of incorrect manual assessments. Early diagnosis and intervention are critical for improving patient outcomes and quality life. If a PD patient is incorrectly diagnosed as healthy, the condition may advance and become challenging to manage.

In managing this difficult disease, we propose a multi-stage CNN model that processes brain MRI scans and extracts intricate features related to the structural changes in the brain associated with PD. By training the CNN on a diverse dataset of both PD and control subjects, the model can learn to differentiate between healthy and affected brain structures. Transfer learning techniques and fine-tuning are employed to enhance the model's performance, leveraging pre-trained neural architectures for improved accuracy.

2. Literature Survey

In 2018, researchers developed a CAD-based CNN model to classify brain MRI images of both PD and healthy persons [1]. Despite achieving an impressive accuracy of 96%, progress was hindered by the limitations of the small dataset, which led to concerns of overfitting. [4] The effectiveness of the model can be enhanced using an optimization strategy where machine learning is implemented. Performance of the sidechain network in the blockchain can be improved in these cases using grey wolf optimization (GWO). Most researchers used vocal data for PD detection, for example, Solana-Lavalle [3] and Alshammri [6], to implement k-nearest neighbor (k-NN), decision tree, multi-layer perceptron, support vector machine and Random Forest machine learning algorithms, but the performance of PD detection based on speech analysis is generally limited by background noise in speech recording causing a high number of false alarms and missed detection. W. Wang [5] implemented boosting ensemble method, k-NN, SVM deep learning and machine learning techniques to classify the health of PD patients but due to a lack of data, the targeted accuracy was not achieved. F. Cordella, A. Paffi and A. Pallotti [10] introduced a study to identify PD using handwritten tasks, including drawing and writing: their result achieved an accuracy of 77.6% only, however. In 2019 M. Wodzinski, A. Skalski *et al* [12] introduced a method for Parkinson's disease detection, using vowels; ResNet's image classification architecture applied audio spectrograms. They used a dataset of 100 patients and achieved 90% accuracy. In a study by Prabhavathi, K. in 2022, [8] researchers used comparative studies of machine learning algorithms such as Support Vector Machine (SVM), Random Forest, k-NN, and Logistic Regression, in which Random Forest was most effective with a detection accuracy of 91.83%. The study's findings may be constrained, however, due to the size and diversity of the MDVP audio dataset. It also only relies on audio data which may potentially ignore early indicators of PD present on non-audio modalities.

Collectively, these studies for early detection of Parkinson's disease are based on or implemented using vocal features, gait and handwritten tasks; data and algorithms used are mostly SVM, k-NN, Random Forest, Decision trees, etc. Research where primarily CNN algorithm is used are subject to the drawbacks of a limited dataset and a reduction in accuracy.

CNNs are effective for medical image analysis and can be trained to recognize damaged brain neurons or structural changes in the substantia nigra and other relevant brain areas by analyzing patterns and features in MRI images. CNN architecture was utilised in the study as it is able to learn complex patterns in images and identify the hidden patterns and trend of data.

3. System Architecture

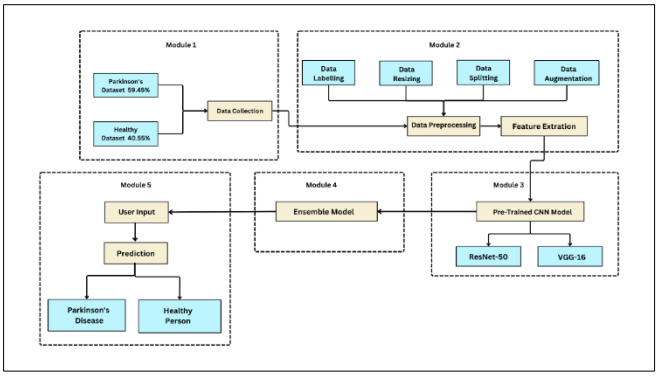

Figure 1. System Architecture

The above figure 1 shows flow of system architecture diagram of proposed system and implementation steps.

3.1 Input dataset: This is the dataset of brain MRI images that will be used to train and evaluate the deep learning model. The dataset should include images from both PD patients and healthy controls.

3.2 Preprocessing of PPMI dataset: This step involves cleaning and preparing the PPMI dataset for use in the deep learning model. This may involve tasks such as DCM to JPG conversion, image resizing, data labelling, data splitting and data augmentation.

3.3 CNN models: We are using two pretrained models - ResNet50 and VGG16. Convolutional layer: This layer is

made up of a number of filters. A filter is a small matrix of weights, whilst the convolution operation is used for extracting features from the input images. Its output represents the features extracted from input images.

Pooling layer: This layer aggregates the values of nearby pixels by minimizing the dimensions of the feature map. It reduces the complexity of the model and improves its robustness to noise.

Fully Connected Layer: The neurons in this layer are interconnected with every neuron in the previous layer. The outcome of the fully connected layer is a probability distribution over the PD or healthy control classes.

3.4 Ensemble Model: An ensemble model often emerges by combining the strengths of ResNet-50 and VGG-16 algorithms.

3.5 Prediction: This is the output of the system, which is the predicted class label for the input image. Input image is the brain MRI image that will be used to make a prediction about whether or not the individual has PD.

4. Methodology

Our methodology is based around an explanation of the model implementation process in which the brain MRI scan images are used as input and are preprocessed with image conversion, data labelling and resizing, data splitting and data augmentation methods. After preprocessing, we used the bagging ensemble method as shown in figure 2 for accurate prediction.

Dataset acquisition:
In the proposed system, the dataset is gathered from the Parkinson's Progression Markers Initiative (PPMI). In the one we are specifically using, the dataset contains a total number of 31,436 MRI scans in the Digital Imaging and Communication in Medicine (DICOM) format. Within this dataset, there are 18,690 MRI scans related to Parkinson's Disease (PD) and 12,746 scans representing Healthy Controls (HC).

Preprocessing:
Data preprocessing is a crucial stage in which raw data is refined and converted into a more comprehensible format. To prepare this data for our model, we initially converted the DCM images into JPG format and resized them uniformly to dimensions of 64x64 pixels and subsequently applied labeling to the images, ensuring that they were properly annotated and interpretable by our deep learning model. As part of our data preprocessing pipeline, we implemented a data splitting technique. As shown in the figure 3, we employed data augmentation techniques on the training dataset, effectively increasing its size and diversity. This augmentation strategy enabled our model to train on a broader range of images, enhancing its ability to recognize and classify patterns.

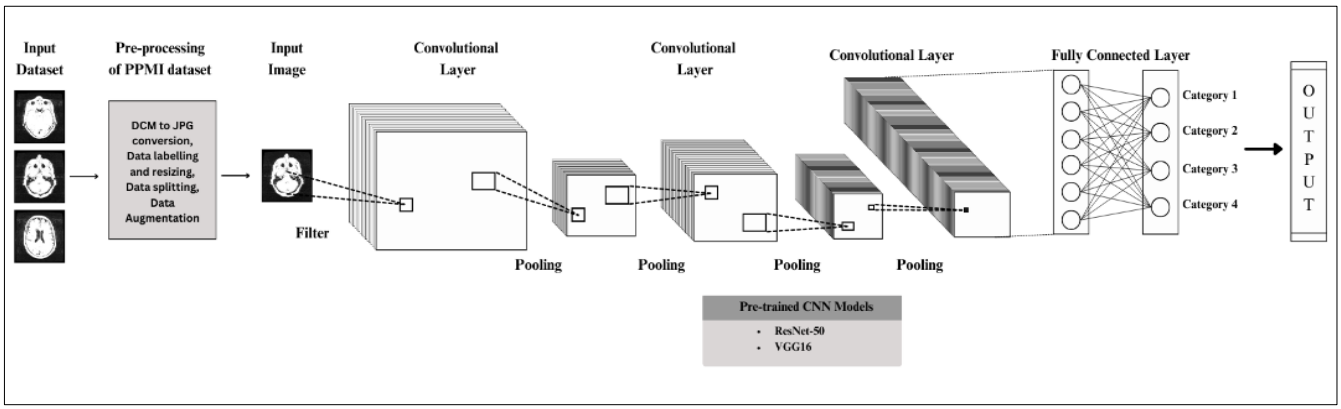

Figure 2. Model Implementation

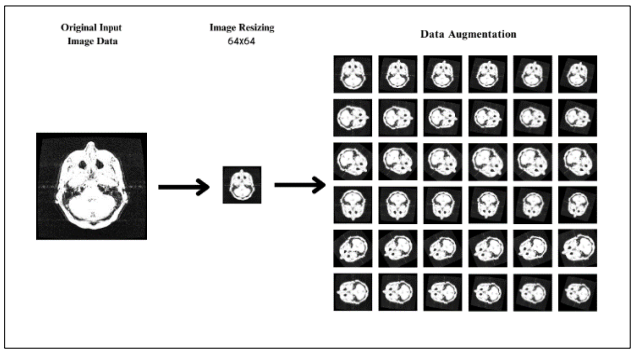

Figure 3. Data Augmentation

Model training:

The training of our CNN model for PD detection is guided by a set of crucial parameters and strategies. We maintained the 'weights shuffle' parameter at 'True' to ensure ongoing robust learning. Our 'batch size' remains fixed at 32, facilitating efficient data processing during training. The model continues to refine its weights over a span of 32 training epochs, and we allocated a 'validation split' of 10% to safeguard against overfitting. Input dataset is divided into three proportions: 80% for training, 10% for validation and 10% for testing.

Fine tuning:

Fine-tuning is used for adjusting a pre-trained model for a specific task or dataset, adjusting parameters until the model achieves the desired accuracy. This technique capitalizes on transfer learning, harnessing the model's prior knowledge while adapting it for PD image analysis.

Convolutional Neural Network (CNN):

Parkinson's disease primarily affects the substantia nigra, a part of the human midbrain responsible for the production of dopamine. CNNs are effective for medical image analysis and can be trained to recognize damaged brain neurons or structural changes in the substantia nigra and other relevant brain areas by analyzing patterns and features in MRI images. Therefore, CNN architecture was used as it is able to learn complex patterns in images and identify hidden patterns and trend of data. CNNs consist of convolutional layers, pooling layers, and fully connected layers. In the convolutional layer, features like edges, shapes and textures are extracted by applying filters on the input image. The output of this layer is served as the input for the pooling layers. The function of the pooling layer is to keep the important features by reducing the dimensions of the image. Afterwards, to predict and classify the input image, the results from the pooling layers are transmitted to fully connected layers.

In our figure 4 CNN model, the first functional layer is based on VGG16, and the second functional layer is derived from ResNet50. In an average layer, an ensemble model often emerges by combining the strengths of ResNet-50 and VGG-16 algorithms. The optimization of model attributes, such as weights and learning rates, is facilitated by the Adam optimizer. To prevent overfitting, the Early Stopping callbacks function from Keras is implemented. After training, the model is saved so that it can be used later to make predictions in the future.

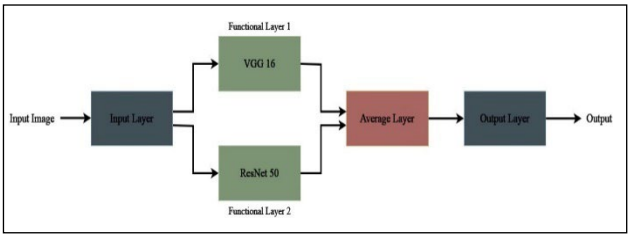

Figure 4. CNN Model

5. Result and Analysis

These models collectively achieved an outstanding accuracy rate of 97%. Leveraging the deep learning capabilities of ResNet-50 and VGG16, we harnessed their unique strengths to extract intricate patterns from medical images, enabling precise identification of early-stage Parkinson's disease. The input image uploading is possible on the system, and the system gives an appropriate output regarding whether the model diagnoses the person with PD or not. To validate our model performance, we also used the new unseen sample images, via which our system was able to predict the result accurately. It is safe to say that our model also works on unseen data accurately. Figure 5 shows the output of new sample data.

For PD patient:

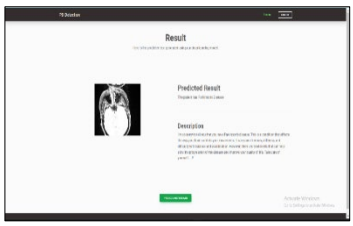

Figure 5. For PD patient

For Healthy patient:

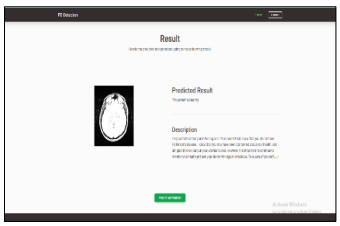

Figure 6. For Healthy

Comparison Table:

To validate our model performance, we test our model by applying various algorithms and activation functions as referred to in table 1. By analyzing the achieved accuracies by the different algorithms and activation functions we come to the conclusion that VGG16 and ResNet50 pre-trained CNN algorithms and ReLu and Sigmoid activation functions gives more accuracy and promising results.

Table 1. Comparison Table

Sr. No.	Algorithm used	Activation Function	Accuracy (%)
1	VGG-16 ResNet-50 EfficientNetB0	Softmax Sigmoid	0.54
2	VGG-16 ResNet-50 EfficientNetB1	Softmax Sigmoid	0.58
3	VGG-16 ResNet-50	ReLu Sigmoid	0.97

Ensemble Model:

Figure 7 shows the bagging ensemble model that are used in Parkinson's disease detection to combine multiple models' predictions, improving performance and robustness. They leverage the strengths of different algorithms or variations, providing more accurate and reliable predictions, crucial in healthcare applications like disease diagnosis.

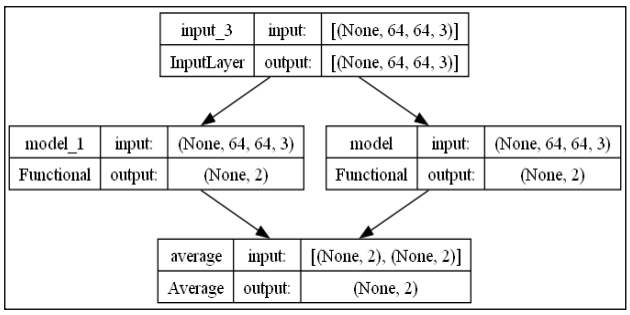

Figure 7. Bagging Ensemble Model

Confusion Matrix:

We used confusion matrix for the evaluation of our CNN based prediction model. It determines the model's performance on a test dataset by analyzing the predicted outcomes. The matrix represents the relationship between actual and predicted classes and helps in examining the better performance of model regarding metrics including precision, recall, accuracy, and F1 score. In the result of confusion matrix we attain the values 32, 36, 5, and 0 for true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) respectively.

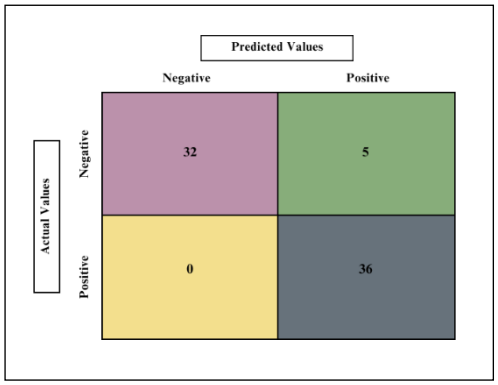

Figure 8. Confusion Matrix

By assessing the TP, TN, FP, and FN distribution, researchers and healthcare professionals can obtain perspectives about a model's accuracy and its capacity to reduce misclassifications, which is critical in the context of disease diagnosis.

$$Precision = \frac{TP}{TP+FP} \qquad Recall = \frac{TP}{TP+FN}$$

The F1 score combines these two metrics into a single value, striking a balance among recall and precision. It is calculated as:

$$f1\ score = \frac{2}{1/Precision + 1/Recall}$$

$$= 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

The F1 provides a balanced assessment of a model's precision and recall, making it particularly relevant in medical diagnostics like PD detection, where both false negatives and false positives can have significant consequences.

Precision (Positive Predictive Value): This component of the F1 score calculates the accuracy of positive predictions. In the context of PD detection, precision assesses the amount of precisely determined PD cases among the total cases predicted as PD. A higher precision indicates fewer false positive predictions, which is essential for minimizing misdiagnoses.

Recall (Sensitivity): The recall evaluates how well the model can detect all true positive instances. PD detection quantifies the ratio of correctly identified PD cases to all

true PD cases. A higher recall implies fewer false negatives, ensuring that actual PD cases are not missed.

Support: Support can be defined as the model's performance for actual occurrences of each class in the test dataset.

The following table 2 shows the classification report generated by our model it helps in understanding the model's strength and weaknesses in identifying and differentiating between classes.

Table 2: Classification report

	Precision	Recall	F1-score	Support
0	1.00	0.86	0.93	37
1	0.88	1.00	0.94	36
Accuracy	-	-	0.93	73
Macro avg	0.94	0.93	0.93	73
Weighted avg	0.94	0.93	0.93	73

In this section, the figure 9 shows the graph of the difference between training loss (0.13) and validation loss (0.65). And the figure 10 shows the graph of the difference between training accuracy (0.97) and validation accuracy (0.84).

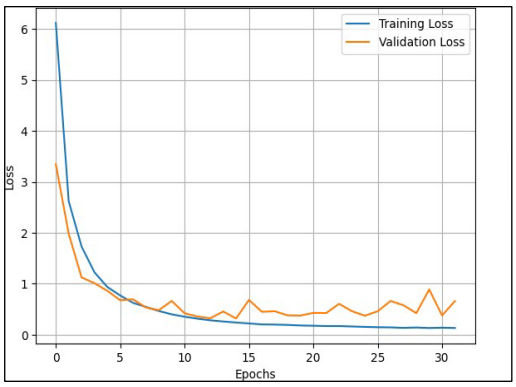

Figure 9. Training vs Validation Loss

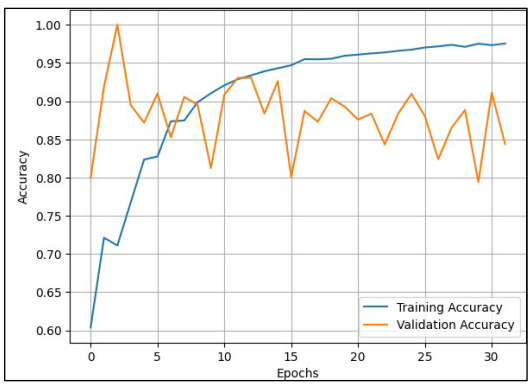

Figure 10. Training and Validation Accuracy

Future Scope

One key future scope is to extend the model's capabilities by incorporating multi-modal data, including not only brain MRI images but also patient clinical data, genetic information, and vocal features. By integrating these diverse data sources, the model can provide a more comprehensive and accurate diagnosis, potentially revolutionizing early PD detection.

Continuous monitoring of disease progression is an intriguing future scope. Extending the model's capabilities to track PD progression over time can assist in personalized treatment planning and optimization of patient care.

Conclusion

In conclusion, this research introduces an innovative framework for the early detection of Parkinson's disease using convolutional neural networks. Our system demonstrates a remarkable capability to identify subtle patterns indicative of PD in its early stages. By leveraging the strengths of the advanced CNN architectures ResNet50 and VGG16, our developed model showcases promising results, emphasizing the significance of deep learning techniques in medical imaging. Our work holds the potential for revolutionizing clinical practices and improving patient outcomes, unveiling exciting opportunities for medical image analysis, whilst empowering researchers and medical teams to engage in feature selection and classification.

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