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Advanced Deep Learning Strategies for Parkinson's Disease Forecasting: Harnessing Convolutional Neural Networks for Proactive Diagnosis

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Abstract: *The Parkinson's disease (PD), an incurable neurological disorder characterized by degeneration of nerve cells in the brain affecting mainly voluntary movements and coordination, gradually worsens over time. Promptly identifying issues ensures better health outcomes for patients while delaying illness advancement. Nevertheless, identifying Parkinson's disease proves difficult because it shares symptoms with several neurologic conditions, resulting in about 25 percent of initial assessments being inaccurate. Deep neural networks like Convolutional Neural Networks excel in categorizing and analyzing medical images due to their capability to autonomously identify complex spatial elements and concealed information structures. Our study introduces a sophisticated machine learning algorithm utilizing convolutional neural networks for identifying if someone has Parkinson's disease automatically. This software employs data sourced directly from the PPMI initiative, an open resource comprising MRI images taken of people diagnosed with Parkinson's disease as well as those without symptoms. This data set includes 31,436 MRIs; among them, 18,690 correspond to patients diagnosed with Parkinson's disease while 12,746 relate to individuals without neurological disorders. To conduct training exercises, the dataset was split into three parts: an 80%-portion used exclusively for learning models, while another 10% served as a test set to evaluate model performance accurately, leaving behind only 10% of the data specifically designated for validating how well the algorithms perform during this phase.*

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

1.Introduction

The Parkinson's disease (PD), characterized by its complexity and lack of curability in neurology, affects numerous people worldwide. The condition known today as Parkinson's disease was initially identified through medical research presented in "An Essay on the Shaking Palsy," authored by Dr. James Parkinson in 1817. The chemical dopamine acts as an intermediary for neural signaling within the central nervous system, facilitating interactions among neurons while also influencing bodily functions such as motor control and coordination. The majority of Parkinson's cases are identified among individuals over sixty; nevertheless, onset may be observed at any stage beyond infancy.

Parkinson's disease primarily manifests through motor impairments such as trembling hands, rigid muscles, difficulty in moving smoothly, and loss of balance when standing up. Beyond physical challenges, individuals frequently encounter conditions like insomnia, mental deterioration, and forgetfulness alongside their mobility issues. Despite not having an immediate solution for Parkinson's disease, various therapies exist to manage symptoms and enhance patient well-being significantly. This encompasses pharmaceutical interventions, exercise regimens like physiotherapy, communication therapies including speech and occupational therapy sessions, alongside medical operations involving techniques like deep brain stimulation surgery.

Variations in Parkinson's disease progression across patients exist, characterized by fluctuating symptoms which usually develop slowly over time; frequently, initial manifestations remain undetected initially. Typically, clinical diagnoses encompass an integration of examining past health information, assessing brain function through tests like those for Parkinson's disease medication effects, alongside observing how patients react when given dopamine-related drugs. Nevertheless, pinpointing correct diagnoses proves difficult owing to overlapping symptomatology between Parkinson's disease and various neurologic conditions, resulting in approximately twenty-five percent error rates among clinical evaluations. Promptly identifying issues early on prevents worsening conditions which become harder to control over time.

Our research introduces an advanced CNN architecture divided into multiple stages aimed at examining brain MRIs for identifying subtle differences indicative of Parkinson's disease through feature extraction.

Through extensive training using data sets including patients with Parkinson's disease and unaffected individuals, convolutional neural networks develop an ability to differentiate between typical and abnormal neurological features in brains. In order to boost classification effectiveness, our approach involves leveraging

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pre-trained neural networks through transfer learning and fine-tuning techniques, resulting in enhanced model precision and broader applicability.

2.Literature Survey

1. In a 2018 study published on ResearchGate, researchers developed a CAD-based CNN model to classify brain MRI images of PD and healthy person. Despite achieving an impressive accuracy of 96%, their progress was hindered by the limitation of a small dataset, which led to concerns of overfitting.
2. In a study published in 2018, titled "Detection of Parkinson Disease in Brain MRI using Convolutional Neural Network," a customized CNN architecture based on Computer-Aided Diagnosis (CAD) was proposed. This approach demonstrated promise in classifying MRI images indicative of PD and healthy. However, the study faced challenges associated with a limited dataset, which led to concerns of overfitting, despite achieving an accuracy rate of 96%.
3. Moving forward to 2020, another study titled "Automatic Parkinson's Disease Detection at Early Stages as a Pre-diagnosis Tool by Using Classifiers and a Small Set of Vocal Features" explored the use of classifiers such as KNN, multi-layer perceptron, SVM and random forest. This research leveraged vocal features as potential biomarkers. Nevertheless, the analysis was constrained by ambient noise in the dataset, resulting in wrong predictions, albeit achieving an accuracy of 94.7%.
4. The performance of the model can be enhanced using an optimization strategy
5. when machine learning is implemented. The performance of the sidechain network in the blockchain is improved in this case using grey wolf optimization (GWO).
6. Collectively, these studies underscore the progress made in leveraging advanced technologies like CNNs and ML algorithms.

3. System Architecture

- 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.
- Pre-processing 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.
- Input image: This is the brain MRI image that will be used to make a prediction about whether or not the individual has PD.
- CNN models: We are using two pretrained models - ResNet50 and VGG16.
- Filter: A filter is a small matrix of weights and the convolution operation used for extracting features from the input images.
- Convolutional layer: This layer is made up of a number of filters. Its output represents the features extracted from input images.
- Pooling: This layer aggregates the values of nearby pixels by minimizing the dimensions of the feature map. It reduces 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.
- Category: This is the output of the system, which is the predicted class label for the input image.

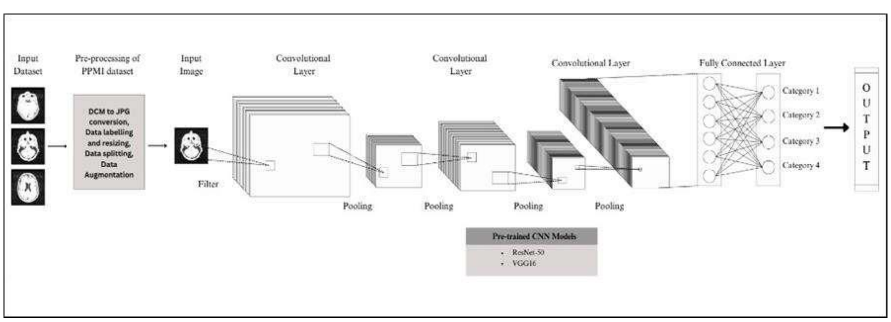

Fig.1 Diagram of disease detection model using CNN

4.Methodology

4.1 Dataset acquisition:

In proposed system, the dataset is gathered from the Parkinson's Progression Markers Initiative (PPMI). We are Specifically using, the dataset containing a total no of 31,436 MRI scans in the Digital Imaging and

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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).

4.2 Preprocessing:

Preprocessing of input data plays a crucial role by converting unorganized information into organized and useful form necessary for effective modeling tasks. For this research project, DICOM(DCM) files initially underwent conversion into JPEG formats before being standardized in size to 64x64 pixels for uniformity within the data set. The images were subsequently carefully tagged so as to enable precise understanding by the advanced machine-learning algorithm. In preparation for evaluating models effectively, the data set underwent division into three categories: training, validation, and testing sets. Additionally, enhancements in the dataset through augmentations helped increase both quantity and diversity of examples during model development. The enhancement procedure made the algorithm more versatile by introducing diverse images into it, which boosted its ability to generalize across different scenarios and improved accuracy when identifying and categorizing symptoms related to Parkinson's disease.

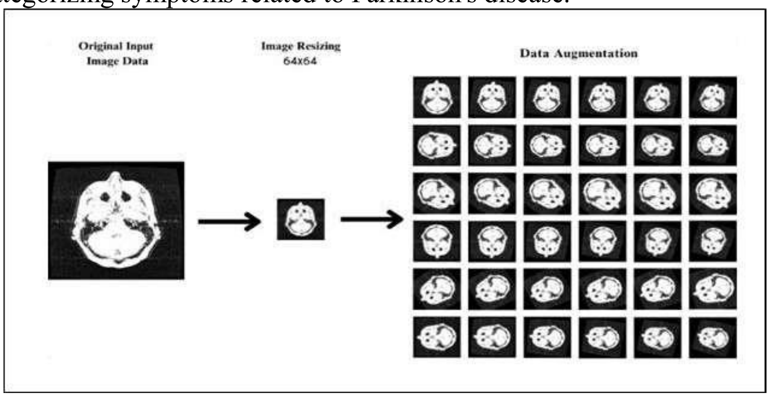

Fig.2 Data Augmentation

4.3 Model training:

A customized neural network model trained on PD data employed meticulously chosen settings and advanced tuning methods. A flag indicating true for the 'weights. shuffle' setting ensures resilient training through avoidance of reliance on input sequence sequencing. Thirty-two instances were employed as an optimization for quick processing and consistent adjustments in learning rates throughout the model's development phase. A simulation underwent training over 32 iterations, enabling gradual enhancement of its hidden parameters and optimization in predictive performance. By incorporating a 10%-validation set into the training phase, we aimed to mitigate overfitting while maintaining dependable outcomes. In total, the data set was divided into three parts 80 percent for training purposes, 10 percent for validating the model's accuracy, and another 10 percent reserved solely for assessing its final testability; and this approach guarantees an even assessment across all aspects of the algorithm's effectiveness.

4.4 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.

4.5Convolutional Neural Network (CNN):

Convolutional Neural Networks (CNNs) are highly effective for medical image classification and analysis due to their ability to automatically learn complex spatial patterns and detect subtle features within imaging data. A typical CNN architecture comprises three main components: convolutional layers, pooling layers, and fully connected layers. The convolutional layers apply filters to the input images to extract essential features such as edges, shapes, and textures. The resulting feature maps are then passed to the pooling layers, which reduce the dimensionality of the data while retaining the most significant information. Finally, the fully connected layers process these extracted features to perform prediction and classification of the input images.

The initial component of the suggested Convolutional Neural Network employs the VGG16 design pattern, whereas the subsequent segment follows the framework outlined by ResNet50. A combined strategy utilizes the capabilities of both VGG16 and ResNet50 architectures, thereby boosting the comprehensive performance evaluation metric for this system. Parameters such as weight values and learning speeds are fine-tuned through application of the Adam optimization algorithm. By employing the Early Stopping

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feature provided by Keras during model training, we aim to prevent overfitting. Following the conclusion of the training stage, the ultimate model is stored specifically for subsequent applications aimed at forecasting and categorizing instances related to Parkinson's disease.

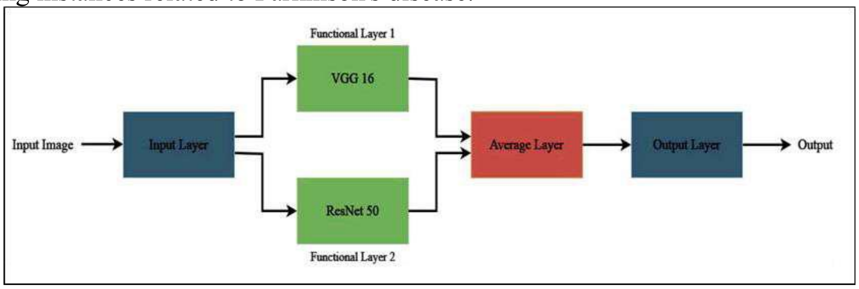
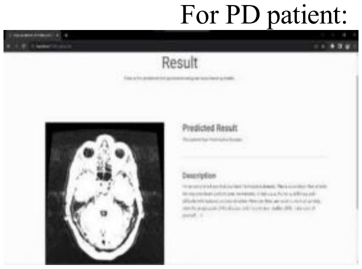


Fig.3 CNN Model

For PD patient:



For Healthy patient:

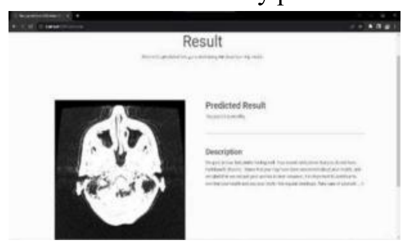


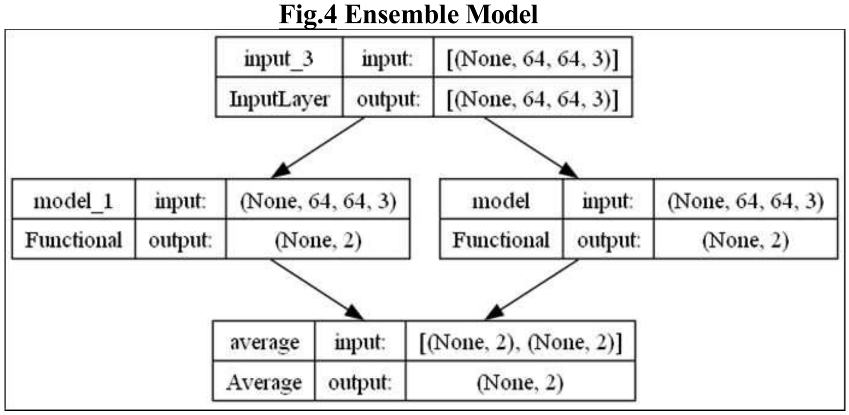
Table1. Comparison Table

SrNo.	hm used	Accuracy
1.	VGG-16 ResNet-50 EfficientNetB0	0.54
2.	VGG-16 ResNet-50 EfficientNetB2	0.58
3.	VGG-16 ResNet-50	0.97

Ensemble Model:

Ensemble models 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.

Fig.4 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.

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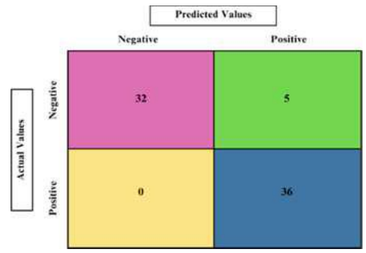


By assessing the of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) distribution, researchers and healthcare professionals can obtain perspectives about model's accuracy and its capacity to reduce misclassifications, which is critical in the context of disease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

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

$$TP$$

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 the terms false negatives and false positives can have significant consequences.

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

$$f1\,scor = \frac{2}{1/precision + 1/Recall}$$

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

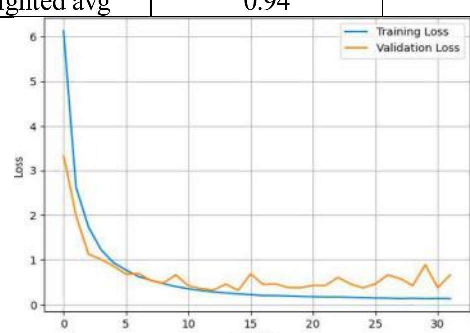
In PD detection with CNNs:

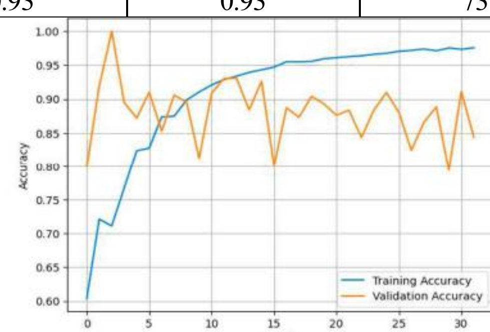
Precision (Positive Predictive Value): This component of the F1 score calculates the accuracy of positive predictions. In the context of PD detection, precision assesses the amount of precisely determined PD cases among the total cases predicted as PD. A higher precision indicates fewer false positive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

Recall (Sensitivity): The recall evaluates how well the model can detect all true positive instances. PD detection, it quantifies the ratio of correctly identified PD cases to all the true PD cases. A higher recall implies fewer false negatives, ensuring that actual PD cases are not missed.

Table 3: 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





6. 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 optimize patient care.

7. Conclusion

In conclusion, our system demonstrates a remarkable capability to predict Parkinson's illness in its earlier stages, addressing a critical need in medical diagnostics. By fine- tuning key parameters such as kernel size, layers, neurons, and epochs, we can optimize the model, mitigating bias and overfitting concerns. This Deep Learning-based approach opens up exciting opportunities for medical image analysis, empowering researchers and medical teams to engage in feature selection and classification. Ultimately, our model holds the potential to revolutionize PD prediction, providing valuable insights for early intervention and improved patient care. The intersection of deep learning and medical imaging promises a brighter future in the quest to combat Parkinson's disease effectively.

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