PARKINSON'S DISEASE DETECTION USING DEEPLEARNING

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ABSTRACT

Parkinson's disease, the second most prevalent degenerative disorder stemming from the loss of dopamine-producing neurons, primarily affects the substantia nigra region, resulting in a deficiency of dopamine in the striatum, which is a key characteristic of the disease. Clinical diagnosis encompasses a spectrum of both motor and non-motor symptoms. Magnetic Resonance Imaging (MRI) serves as a tool to visualize structural changes in the brain due to dopamine deficiency in individuals with Parkinson's disease. This study employs deep learning techniques, specifically the Convolutional Neural Network architecture Resnet, to classify MRI images of healthy controls and Parkinson's disease patients. By training the network with transfer learning, the model can accurately distinguish between the two groups, achieving an accuracy of 91.9%. This approach demonstrates the potential for deep learning models to aid clinicians in Parkinson's disease diagnosis, offering an objective and improvedmethod for patient classification in the future.

INDEX TERMS: *Parkinson's disease, Deep learning, Ensemble learning, Early detection, Premotor features, Features importance*.

INTRODUCTION:

Parkinson's Disease (PD) is a complex neurodegenerative disorder that affects millions of people worldwide, leading to significant challenges in mobility, cognition, and overall quality of life. Characterized by the progressive loss of dopaminergic neurons in the substantia nigra region of the brain, PD manifests through a range of motor symptoms such as tremors, rigidity, bradykinesia, and postural instability, along with non-motor symptoms like cognitive impairment, depression, and sleep disturbances. Early and accurate diagnosis of PD is crucial for timely intervention and personalized treatment strategies that can slow disease progression and alleviate symptoms.

Medical imaging techniques, particularly Magnetic Resonance Imaging (MRI), play a pivotal role in assessing brain structure and function, aiding in the diagnosis and monitoring of neurological disorders like PD. MRI offers detailed anatomical information and enables clinicians to visualize changes in brain morphology, volume, and connectivity associated with PD pathology. However, manual interpretation of MRI scans for PD diagnosis can be time- consuming, subjective, and prone to inter-observer variability, highlighting the need for automated and objective analysis methods.

In recent years, deep learning algorithms have revolutionized the field of medical image analysis by leveraging large-scale datasets and sophisticated neural network architectures to extract meaningful features and patterns from complex imaging data. Models such as DenseNet169 and ResNet152, renowned for their deep-layer architectures and skip connections, have demonstrated exceptional performance in various computer vision tasks, including object recognition, image classification, and semantic segmentation.

The integration of deep learning techniques with MRI-based PD diagnosis holds immense promise for enhancing diagnostic accuracy, streamlining workflow efficiency, and facilitating early intervention strategies. By harnessing the computational power of DenseNet169 and ResNet152, we aim to develop a robust and reliable framework for automated PD detection from MRI scans, contributing to improved patient outcomes, personalized treatment plans, and a better understanding of disease progression mechanisms.

This study focuses on the application of deep learning methodologies, specifically DenseNet169 and ResNet152, for PD detection using MRI imaging data. Our objectives include:

1. Curating a comprehensive dataset of MRI scans from PD patients and healthy controls, ensuring diversity and representativeness of clinical cases.

2. Preprocessing MRI images to enhance quality, remove noise, and standardize imaging protocols across the dataset, ensuring consistency in feature extraction.

3. Implementing transfer learning techniques to fine-tune DenseNet169 and ResNet152 architectures for PD detection, leveraging pre-trained models on large-scale image datasets like ImageNet.

4. Evaluating the performance of the deep learning models based on metrics such as accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC- ROC).

5. Comparing the effectiveness of DenseNet169 and ResNet152 in distinguishing PD cases from healthy controls, analyzing their respective strengths and limitations in medical image analysis tasks.

6. Validating the robustness and generalizability of the proposed deep learning framework using cross-validation techniques and external validation datasets, ensuring reliable model performance across different patient cohorts and imaging centers.

7. Interpreting the deep learning models' feature representations and highlighting key imaging biomarkers or regions of interest associated with PD pathology, aiding clinicians in diagnostic decision-making and disease understanding.

8. Discuss the clinical implications, challenges, and future directions of deep learning-based PD detection from MRI scans, including potential integration into clinical practice, regulatory considerations, and ongoing research avenues.

Through this research endeavor, we aim to advance the field of neuroimaging and computational neuroscience by harnessing the synergy between deep learning methodologies and MRI technology for more accurate, efficient, and accessible Parkinson's Disease diagnosis and management.

Neuroimaging and Biomarkers: In this protection, informed consent, and this section, we'll examine how cutting-edge needs. neuroimaging methods, such as structural and functional MRI, PET scans, and cerebrospinal fluid biomarkers, maybe

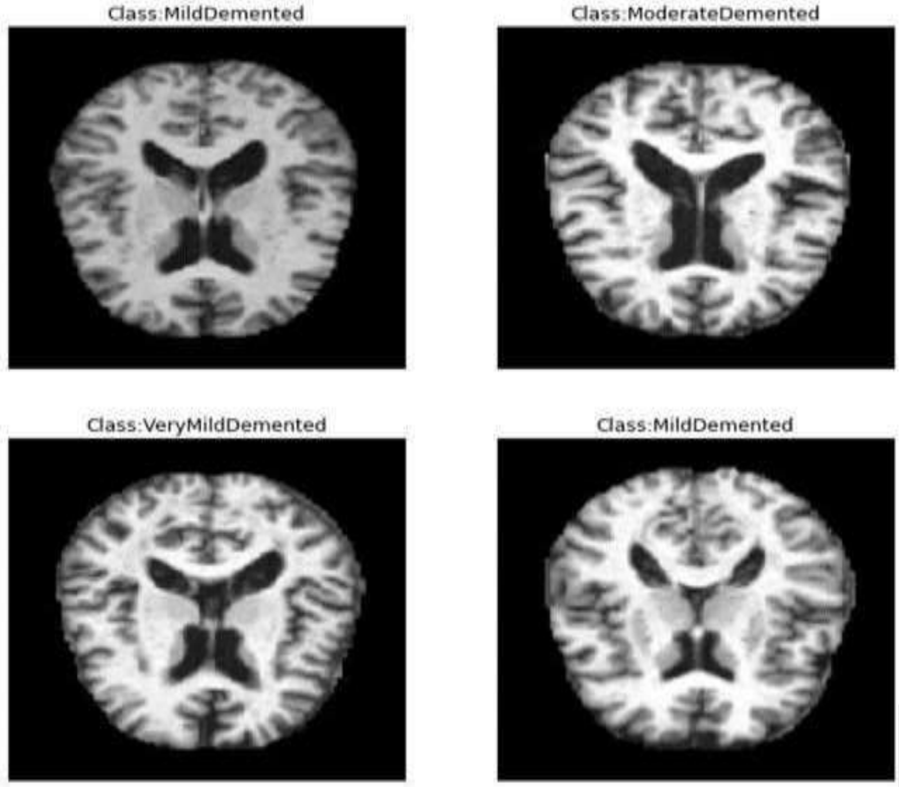
Dataset and Methodology

This section discusses in detail the used dataset and provides visual examples of the data. In addition, all stages of the proposed model with all hyperparameters are also discussedin this section.

Dataset *:*

In this research, the Parkinson’s dataset was utilized, which is a dataset that has been collected by hand and consists of MRI images that have been verified and labeled by experts. The data is divided into four different classes:
Mild Demented, Moderate Demented, NonDemented, and Very Mild Demented. These images can be used to train deep learning models to accurately predict the stage of Parkinson’s disease. The dataset provides an opportunity for researchers to develop algorithms that can accurately diagnose Parkinson’s disease and aid in the development of effective treatments. The dataset is publicly available on Kaggle and is easily accessible. By making this dataset available to the public, the creators hope to encourage more research in the field and support the development of better algorithms for the diagnosis and treatment of Parkinson’s disease. This dataset was chosen for its availability, its different classes, and its small size on a hard disk compared to other common datasets in this field.

Figure 1. Sample image from the database



When working on a multi-classification job with this dataset, we can observe that the class Moderate Demented has a very low amount of photos compared to other classes, which leads to false positives and influences the results. To expand the number of photographs in this class and address the imbalance issue at the same time, we use a data augmentation strategy to resolve this

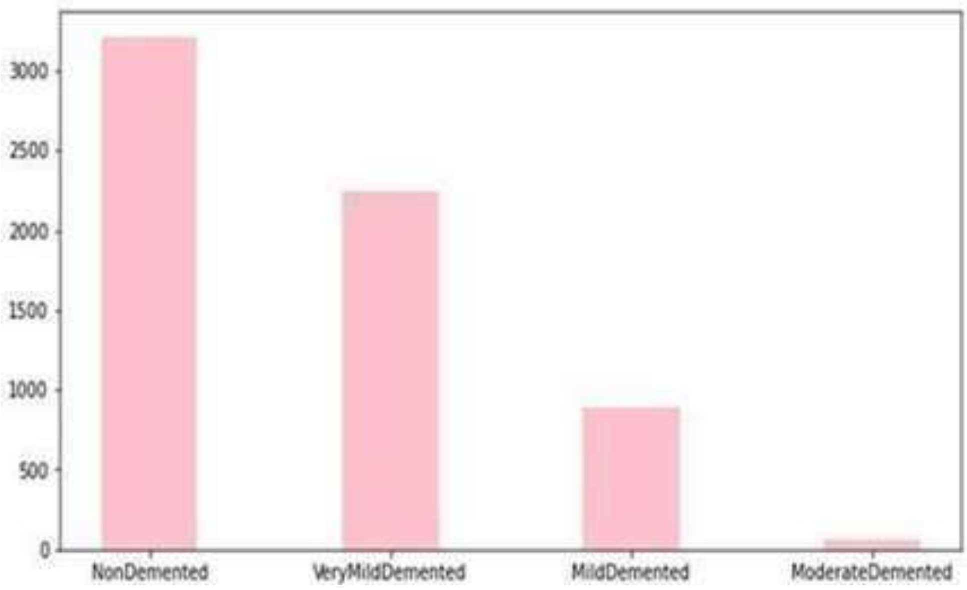


Figure 2. Statistics of the Kaggle Dataset

The main block diagram of our approach is shown in Figure 3, and it is covered in more detailin the next section.

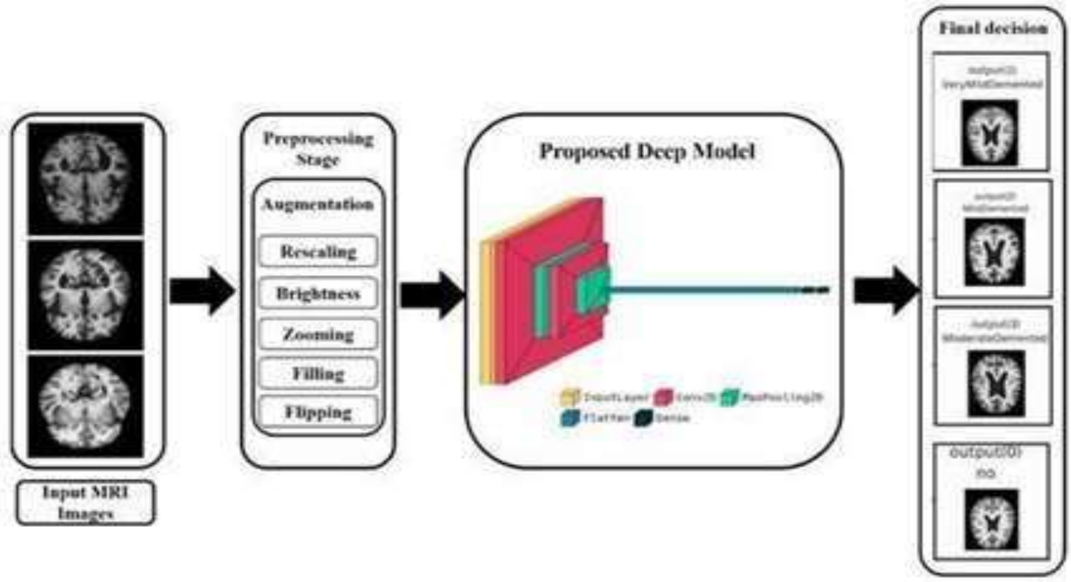


Figure 3. Block diagram of all stages of our method.

2. Preprocessing Stage

In this step, we utilized the Image Data Generator class from the Keras library, which allows for the application of several image augmentation methods to the input data to produce a fresh set of enhanced pictures that can be used for training. The particular augmentation methods used in this research include pixel scaling, brightness modifications, magnification adjustments, constant value filling of newly formed pixels, and random horizontal flipping of pictures. These methods seek to both artificially expand the amount of the training dataset and strengthen the model's resistance to changes in the input data. The input picture data may be fed into our deep model once the Image Data Generator instance has been established, and the enhanced data can then be utilized to train a deep learning model. This process is crucial to ensure that the model can generalize successfully to novel or unexplored data.

3. *Proposed Deep Model for Binary-Classification*

A high-level neural network API called Keras, which is based on TensorFlow, was used to develop the suggested deep learning model [37]. The model is intended for binary classification, to determine whether or not an input picture belongs to a certain class. The visualization of our model for a binary classification challenge is shown in Figure 4. A 150 x 150 x 3 (height, width, and depth) picture that depicts a color image with three channels (red, green, and blue) is the model's first input layer. To extract features from the picture, a succession of convolutional layers (Conv2D) and pooling layers (MaxPooling2D) are applied to the input image. The pooling layers down-sample the feature maps that the convolutional layers output after applying filters to the input picture. The features are then flattened and sent through two dense layers (Dense), which modify the features in non-linear ways by activating them using the 'ReLU' activation function. The final prediction is then generated by the output layer using the sigmoid activation function, which converts the input to a probability-like output between 0 and 1. The model is built using the binary cross-entropy loss function and the 'Adam' optimizer, and it is trained using the fit technique on the training set of data. A loss of 0.061 and an accuracy of 0.993 are shown in the training results, demonstrating the model's capacity to provide precise predictions based on the training data. The executive overview of the suggested binary classification model

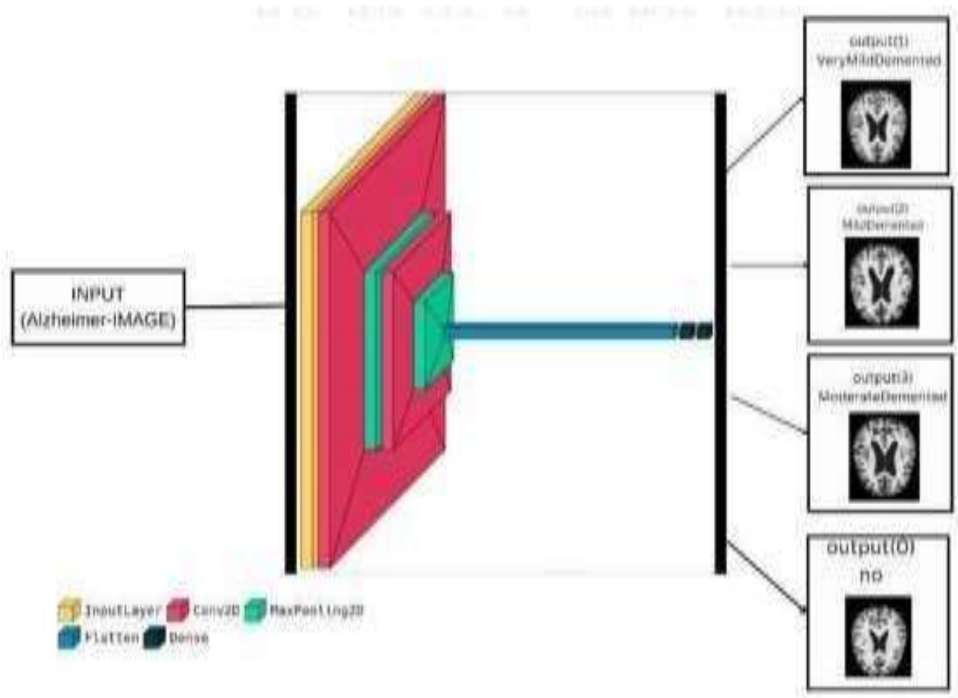


Figure 4. Model visualization to the binary classification task

3.4. Proposed Deep Model for Multi-Classification

The model in this study accepts images of dimensions (150, 150, 3), indicating that each image is 150 x 150 pixels with three color channels (red, green, and blue). The model applies a sequence of Conv2D and MaxPooling2D layers to decrease the spatial dimensions of the image and extract significant features. These extracted features are then flattened and passed through two dense layers with 'ReLU' and 'SoftMax' activation functions. The 'SoftMax' activation function provides the final probability scores for each class in the classification task. The model is compiled with an 'Adam' optimizer and a categorical cross-entropy loss function. It is trained on the training data for 100 epochs and evaluated on the validation data, achieving an accuracy of 96%. The model's visualization for multi-classification tasks is shown in Figure 6.

Algorithm:

Step 1: BEGIN

Step 2: INPUT: dataset_directory, training_percentage,image_augmentation_parameters,model_ parameters, optimizer, loss_ function, performance_metrics.

Step 3: Load input dataset from dataset_directory

Step 4: Split the dataset into a training set and validation set with training_percentage

Step 5: Instantiate an ImageDataGenerator object with image_augmentation_parametersStep 6:

6.1 IF model_parameters is a pre-trained model THEN

6.2 Load pre-trained model

6.3 ELSE

6.4 Define a deep learning model using Keras with model_parameters

6.5 ENDIF

Step 7: Compile the model using optimizer and loss_function

Step 8: Train the model on the training set for several epochs with the compiled model andImage Data Generator object.

Step 9:

9.1 FOR each epoch in the training process DO.

9.2 Evaluate the model on the validation set using performance_metrics.

9.3 IF the validation accuracy is not improving THEN.

9.4 Reduce learning rate.

9.5 ENDIF.

9.6 ENDFOR

Step 10: Test the final model on a separate test set to evaluate its generalization performance using performance_metrics.

Step 11: OUTPUT is the performance metrics of the proposed method and existing methods for comparison.

Step 12: END

Results

The proposed deep model is trained on the Kaggle dataset through multiple experiments. A standard approach of cross-validation (10-CV) is used for training and testing to ensure a fair and reliable evaluation of the proposed PD detection model. The approach is implemented on a computer equipped with an NVIDIA Tesla T4 GPU and 14 GB DDR4 RAM, using Keras, a Python-based library. The 'Adam' optimizer is applied for training the neural network, with binary cross entropy as the loss function for model 1 and Categorical Crossentropy as the loss function for model 2. Four evaluation measures are used in this study: Accuracy, Precision, Recall, and F1-score.

$$Accuracy = TP+TN/TP+TN+FP+FN \quad (1)$$

$$Precision = TP/TP+FP \quad (2)$$

$$Recall = TP/TP+FN \quad (3)$$

$$F1\text{-}score = 2 \times Precision \times Recall / Precision+Recall \quad (4)$$

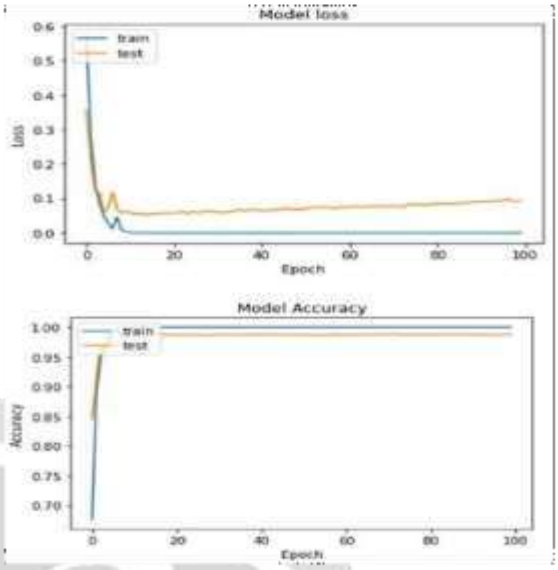
where TP denotes true positives, FP denotes false positives, TN denotes true negatives and FNdenotes false negatives.

Figure 9. Confusion matrix of the proposed method to detect PD for binary classificationtasks.

experiment.

A. The first experiment

The proposed deep model was used to classify input MRI images into two groups for a binary challenge (AD or Normal). The confusion matrix of the proposed approach for detecting AD is shown in Figure 9, where class 0 represents normal instances and class 1 represents AD patients.



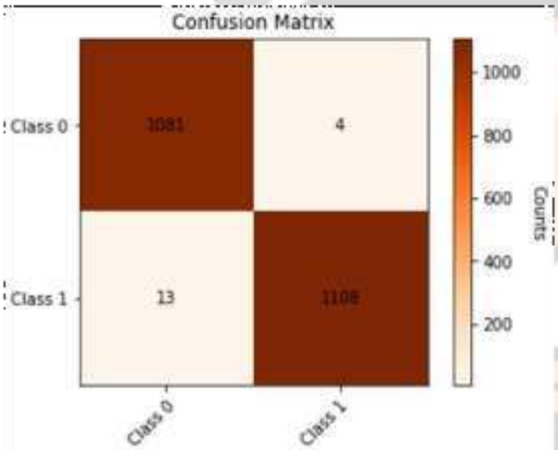


Figure 10. Loss curves (upper) and accuracy curves (lower) for the training and testing data for the proposed model for binary classification task.

B. The second experiment

The proposed deep model was used for multi -classification to categorize input MRI images into four categories: Mild Demented, Moderately

1. Experimental Analysis

In this paper, two experiments are evaluated using four metrics. The first experiment is based on the first model, which is used for a binary classification task. The second experiment is based on the second model, which is used for multiclassification tasks. The paper provides details and analysis of each According to the confusion matrix shown in Figure 10, it can be seen that 1081 normal MRI images were correctly detected as normal, while 0.3% of normal class were detected as PD. Demented, Non-Demented, Additionally, 98% of PD cases were correctly detected as PD, while 13 MRI images were incorrectly detected as normal cases. Very Mild Demented. The confusion matrix of the proposed method for detecting demented cases is shown in Figure 11. In this matrix, Class 0 refers to NonDemented cases, Class 1 refers to Very Mild Demented cases, Class 2 refers to Mild Demented cases, and Class 3 refers to Moderate Demented

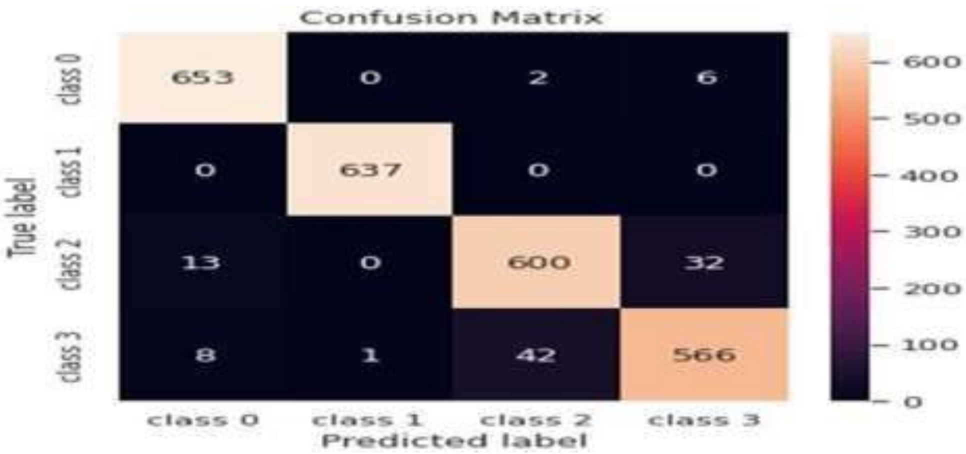


Figure 11. Confusion matrix of the proposed model for the multi-classification task.

According to the previous confusion matrix in Figure 11, 653 Non-Demented cases were correctly detected as NonDemented; 2 MRI images of NonDemented cases were incorrectly detected as Mild Demented cases, and 6 MRI images were correctly detected as Moderately Demented cases. We can also find that 100% of the Very Mild

Demented cases are correctly detected as Very Mild Demented cases. In addition, we can observe that 93% of the Mild Demented cases are correctly detected as Mild Demented, 4.9% of the images are wrongly detected as Moderate Demented, and 2.1% are wrongly detected as Non-Demented cases. Finally, we can also observe the confusion. matrix that 91.7% of the Moderate Demented cases are correctly detected as Moderate Demented, 42 MRI images are wrongly detected as Mild Demented, 1.29% are wrongly detected as Non-Demented cases, and 0.16% of the images are wrongly detected as Very Mild Demented cases.

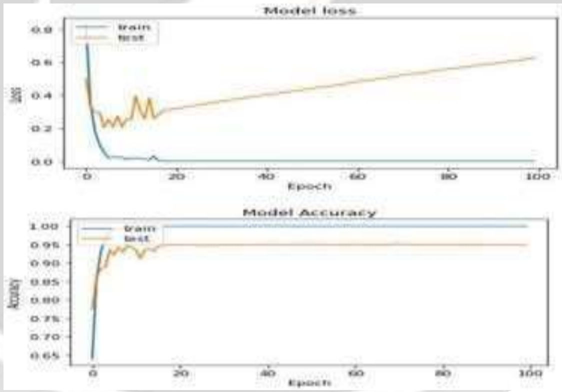


Figure 12. Loss curves (upper) and accuracy curves (lower) for the training and testing data for the proposed model for multi-classification tasks.

DISCUSSION:

Parkinson's disease (PD) early-stage prediction is a hotly debated issue in the world of medical research. Parkinson's disease is difficult to anticipate in its early stages, yet early therapy is more efficient and results in less minor damage than late treatment1. To determine the most accurate parameters for Parkinson's disease prediction, a variety of algorithms including Decision Tree, Random Forest, Support Vector Machine, Gradient Boosting, and Voting classifiers have been used. The Open Access Series of Imaging Studies (OASIS) data is used to generate predictions for Parkinson's disease, and the performance of ML models is gauged using metrics including Precision, Recall, Accuracy, and F1-score. Machine learning (ML), a subfield of Artificial Intelligence (AI), uses various probabilistic and optimization techniques to help computers learn from huge and complicated data sets. To diagnose PD in its early stages, researchers generally use machine learning. The survey provides a broad overview of current research in this field and analyses the classification methods used by researchers working with PDNI data sets. It discusses essential research topics such as the data sets used, the evaluation measures employed, and the machine learning methods used. The proposed classification scheme can be used by clinicians to make diagnoses of these diseases. It is highly beneficial to lower annual mortality rates of Parkinson’s disease in early diagnosis with these ML algorithms. The proposed work shows better results with the best validation average accuracy of 83% on the test data of PD. This test accuracy score is significantly higher in comparison with existing works.

CONCLUSIONS:

The goal of this study is to assess the performance of deep learning models in detecting andclassifying Parkinson's disease (PD) using MRI images. The results obtained in the binary classification task, with an accuracy of 99.30%, and in the four-class classification task, with an accuracy of 95.96%, demonstrate the potential of deep learning models for accurately detecting and differentiating between the different stages of PD. The use of image data with a shape of 150 x 150 x 3, as well as image augmentation techniques and a SoftMax activation function with a dense four-output layer, were found to be critical factors in achieving these results. This study contributes to the growing body of literature on the use of deep learning models for PD detection and classification. Specifically, it demonstrates the potential of using MRI images and deep learning models to accurately detect and classify PD, which has important implications for early diagnosis and treatment. However, some limitations to this study should be considered. The dataset used is relatively small and may not be representative of the entire population. Additionally, only a single modality (MRI images) was considered, and future studies could explore the use of other imaging modalities in combination with deep learning models.
Future work could focus on addressing these limitations and exploring the use of deep learning models in other areas of medical imaging. The development of more explainable deep learning models that can provide insights into the underlying biological mechanisms of PD could furtheradvance our understanding of this disease.

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