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Advanced Deep Learning Techniques for Predicting Neurodegenerative Diseases

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***Abstract*— Two of the most prevalent neurodegenerative disorders affecting the elderly are Alzheimer's Disease (AD)and Parkinson's Disease (PD). AD is a neurological illness that progressively deteriorates a person's cognitive and memory abilities, along with their ability to do daily tasks and enjoy life. Motor signs of PD include tremors, rigidity, and balance problems. In this research, we examine several deep learning algorithms for predicting AD from MRI images and PD from spiral drawings of patients. The research suggests a convolutional neural network (CNN) method that makes use of patients' spiral drawings, a sensitive and non-invasive biomarker, for the prediction of PD. VGG16, a deep learning model, achieves great accuracy for predicting AD, showing the promise of such methods for helping to diagnose and cure neurodegenerative disorders at an earlier stage. The CNN model achieved higher accuracy for PD detection. The application of deep learning techniques in predicting neurodegenerative illnesses is an essential area for further research because early detection and management are crucial for better patient outcomes and an improved quality of life. The findings of this study show the importance of non-invasive biomarkers in illness diagnosis and provide light on the potential of CNN algorithms for AD and PD prediction. Better healthcare outcomes and quality of life for people with neurodegenerative disorders can result from continued study of deep learning-based diagnosis and treatment.**

Keywords—Deep learning, Alzeihmeirs disease, Parkinson's disease, MRI Scan, Spiral images.

I. INTRODUCTION

In the past few decades, neurological diseases like Alzheimer's and Parkinson's have emerged as a severe threat to public health. Patients' lives can be greatly enhanced and the progression of disease slowed with early detection and therapy. Alzheimer's disease (AD) is a form of dementia that causes cognitive decline over time. It's responsible for almost two-thirds of all occurrences of dementia. It's a degenerative illness that might cause modest decline in memory at first and, eventually, the inability to hold a thought or react to your surroundings. The areas of the cerebral cortex responsible for thinking, remembering, and communication are all affected by Alzheimer's disease.It may have a devastating effect on one's capacity to function normally. Most people understand that old age is a factor in developing Alzheimer's disease. Parkinson's illness is a degenerative neurological ailment that mainly impacts the motor system, causing shaking hands, rigidity, and other difficulties with movement over time. Patients with Parkinson's disease benefit greatly from earlier detection and treatment [1,2].

For effective diagnosis of illnesses, deep learning methods have recently been used to healthcare information processing. Better medical results and patient satisfaction can be achieved via timely identification and treatment of certain conditions. Algorithms that accurately forecast neurodegenerative illnesses have been developed thanks to the latest developments in machine learning and deep learning approaches. The use of imaging techniques and biomarkers that are not invasive in deep learning models for the prediction of Alzheimer's and Parkinson's disease has produced encouraging results. These simulations may someday be used as a tool in early identification and management of neurological conditions [3,4].

In this research, we compare and contrast several deep learning models that use magnetic resonance imaging (MRI) images and spiral drawings of patients to make diagnoses of Alzheimer's disease and Parkinson's disease. The research suggests that spiral drawings, a sensitive and non-invasive biomarker, can be used in conjunction with a convolutional neural network (CNN) algorithm to predict Parkinson's disease. To further demonstrate the promise of such methods in aiding in the early detection and treatment of neurodegenerative disorders, we also investigate the application of VGG16, a deep learning model, for predicting Alzheimer's disease, which achieves high accuracy. The MRI scans of people with Alzheimer's disease were used in studies. Both the test set and the training set contain images from the following four categories: very mild demented (VMD), mild demented (MD), moderately demented (MdD), and non-demented (ND). There were 5121 images in the training set and 1279 in the testing set. In the dataset, the image sizes have all been adjusted to 224x224. The Parkinson's disease data utilised in this analysis was retrieved from [6]. The dataset itself is an image collection that has already been divided into a training set and a testing set. Testing and training in a spiral pattern 72 images for training. Images used for testing: 30 The dataset size was increased through data augmentation.

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The contribution of our research is as follows:

- Deep learning algorithms are examined for predicting Alzheimer's disease (AD) from MRI images and Parkinson's disease (PD) from spiral drawings.
- Spiral drawings are explored as a non-invasive biomarker for PD prediction, along with a convolutional neural network (CNN) algorithm.
- VGG16, a deep learning model, is investigated for accurate AD prediction.
- The dataset used includes MRI images of individuals with AD, categorized into different groups, and a separate dataset for PD consisting of spiral pattern images.
- The importance of early detection and management in neurodegenerative disorders is emphasized.
- The findings demonstrate the potential of deep learning-based diagnosis and treatment methods in improving healthcare outcomes for neurodegenerative disorders.

Overall, our research contributes by examining deep learning models, utilizing non-invasive biomarkers, investigating VGG16 for AD prediction, utilizing specific datasets, and emphasizing the importance of early detection and management in neurodegenerative disorders.

The subsequent sections of the paper are structured as follows. Section II provides an overview of the relevant literature concerning the prediction of AD and PD utilizing machine learning and deep learning techniques. Section III details the proposed deep learning methods employed for the detection of AD and PD. Subsequently, in section IV, we present the experiments conducted and the corresponding results obtained. Finally, the paper concludes with a summary of the findings and suggestions for future research directions in this field.

II. Related work

Related work in the field of Alzheimer's disease and Parkinson's disease prediction utilising Machine Learning and Deep Learning is discussed below. The paper [5] explains how to apply deep learning strategies for automatic Alzheimer's disease (AD) categorization based on neuroimaging data. For Alzheimer's disease (AD) categorization and forecasting the transition from mild cognitive impairment (MCI) to AD, the authors provided a comprehensive evaluation of 16 studies published between 2013 and 2018, comparing the use of deep learning and classical machine learning methodologies. These results demonstrate the efficacy of deep learning methods like CNN and Recurrent Neural Network (RNN) for AD classification and MCI conversion prediction without the need for any preliminary processing for identifying traits. The most promising outcomes were achieved by integrating multimodal images with fluid indicators. Finally, they suggested that deep learning algorithms hold potential for clinical categorization of AD using heterogeneous imaging information, with additional enhancements possible through the inclusion of more composite types of data and more openness with comprehensible techniques.

The paper [7] suggests a deep learning architecture for Parkinson's disease diagnosis. The preliminary or premotor phase of PD must be closely watched for accurate diagnosis as soon as possible. Rapid eye movement (REM) sleep behaviour disorder (RBD) and loss of smell are two symptoms that are common throughout this premotor phase but not present during the motor phase. There are two basic phases to PD detection: training and testing. The unprocessed information is cleaned up and standardised during training, after which it is utilised to build the deep learning model. And in the testing phase, the built model is utilised to identify PD using the chosen variables.

Recent research [8] on Alzheimer's disease (AD) and moderate cognitive impairment (MCI) typically rely on a single data method, such as AD stage, for predictive purposes. Individuals were classified into Alzheimer's disease (AD), mild cognitive impairment (MCI), and controls (CN) using deep learning (DL) to integrate analysis of MRI imagery, genomic (one-time sequence variants [SNPs]), and diagnostic test outcomes. They employed 3D-convolutional neural networks (CNNs) for the images, and layered whitening automatic encoders for medical and genealogical information. Support vector machines, decision trees, random forests, and k-nearest neighbours are all examples of shallow models, however the researchers of the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset show that deep models perform better.

The work [9] introduces an innovative deep learning technique to accurately detect Parkinson's disease (PD) at an early stage based on premotor features. By comparing the proposed deep learning model with other methods, the study demonstrates its superior performance with an average accuracy of 96.45%. The research also highlights the importance of features in the PD detection process using the Boosting method. Overall, the study contributes to early PD detection and emphasizes the effectiveness of the deep learning approach.

To classify patients into AD, MCI, and control groups, the authors of [10] recommend utilising deep learning (DL) to analyse numerous data modalities, such as magnetic resonance imaging (MRI), single nucleotide polymorphisms (SNPs), and clinical test data. They developed an innovative data interpretation approach to determine the best attributes learned by the deep models through the usage of stacked denoising auto-encoders and 3D-convolutional neural networks (CNNs). By comparing their deep learning models against the likes of support vector machines, decision trees, random forests, and k-nearest neighbours, the authors show that their work is superior, and that incorporating multi-modality data leads to significant performance improvements. Brain regions like the hippocampus and amygdala, as well as the Rey Auditory Verbal Learning Test (RAVLT), are among the most distinctive aspects determined by the models, and they are in line with what is already known about AD.

Research [11] focuses on the early diagnosis and categorization of Alzheimer's disease (AD) using deep learning techniques. Synthetic MRI images generated by cascading Deep Convolutional Generative Adversarial Networks (DCGANs) and enhancing resolution with Super-Resolution Generative Adversarial Networks (SRGANs) show promise in improving classification and prediction accuracy. Another study [12] reviews various conventional machine learning methods applied to AD classification and prediction using MRI data, discussing challenges and suggesting approaches for pre-processing and model

selection. Parkinson's Disease (PD) detection is addressed in research [13], utilizing different machine learning and deep learning models for distinguishing healthy and PD patients based on voice signal features. The study achieves high accuracy using Multi-Layer Perceptron (MLP) and Support Vector Machine (SVM) models. Similarly, research [14] focuses on AD detection through neuroimaging data, utilizing algorithms and models like VGG-16 and Improved Faster Recurrent Convolutional Neural Network (IFRCNN) for image categorization. Lastly, a framework for dementia prediction using data from the OASIS project is proposed in [15], employing various machine learning algorithms for classification and achieving high accuracy using Support Vector Machine (SVM) with full features. Table 1 shows the comparative analysis of the proposed work with the existing works.

TABLE I. Comparison of proposed work with the existing works

Research work	**Focus**	**Methodology**	**Key Findings**
Proposed Work	AD and PD prediction using deep learning	Deep learning with premotor features	Examined deep learning algorithms for AD and PD prediction from MRI images and spiral drawings. CNN achieved high accuracy for AD and PD prediction. Highlighted the importance of non-invasive biomarkers and potential of deep learning in neurodegenerative disorder diagnosis..
[5]	Alzheimer's disease (AD) categorization	Deep learning compared to classical machine learning	Deep learning methods like CNN and RNN showed efficacy in AD classification and MCI conversion prediction without preliminary processing. Integration of multimodal images with fluid indicators improved outcomes.
[7]	Parkinson's disease diagnosis	Deep learning architecture	Identified symptoms common in premotor phase (REM sleep behavior disorder and loss of smell) for accurate PD diagnosis. Employed deep learning model using selected variables for PD identification.
[8]	Neurological disorder detection (Alzheimer's, Parkinson's, schizophrenia)	Comparative analysis of DL methods	Convolutional Neural Network outperformed other methods in detecting neurological disorders from MRI data. Highlighted challenges and suggested future research directions.
[9]	Early detection of Parkinson's disease	Deep learning with premotor features	Introduced innovative deep-learning technique for early PD detection. Achieved superior detection performance with highest average accuracy of 96.45%. Considered multiple indicators for early PD detection.
[10]	Alzheimer's disease classification	Deep learning with multi-modal data	Utilized deep learning models with MRI, SNPs, and clinical test data. Showed superior performance compared to other machine learning methods. Identified distinctive brain regions and test scores related to AD.
[11]	AD prediction	Deep learning (DCGAN, SRGAN)	Synthetic MRI images achieve 99.7% accuracy in AD prediction
[12]	AD classification	Conventional machine learning (SVM, RF, CNN)	Review of various methods and challenges in AD classification
[13]	PD detection	Machine learning (MLP, SVM, RF, DT, KNN)	MLP achieves 98.31% accuracy in PD detection using voice signal features
[14]	AD identification	Automated algorithms (VGG16, IFRCNN)	98.32% accuracy in AD identification using neuroimaging data
[15]	Dementia prediction	Machine learning (Adaboost, DT, RF, SVM)	SVM achieves 96.77% accuracy in dementia prediction using imaging data

The proposed work introduces novel elements compared to existing works in the field of neurodegenerative disorder prediction. It integrates multiple data modalities, including MRI images and spiral drawings, to enhance accuracy and provide a comprehensive understanding of diseases. The focus on non-invasive biomarkers, such as spiral drawings, offers a promising avenue for early detection without invasive

procedures. Additionally, the work compares deep learning algorithms against traditional methods, highlighting the superior performance of the designed model. Emphasizing the practical implications, the study underscores the importance of early detection and management for improved patient outcomes. Overall, these contributions bring novelty to the field and provide valuable insights for further research and healthcare applications.

III. PROPOSED METHODOLOGY

The proposed methodology for the precition of Alzheimer's and Parkinson's Disease using Deep Learning Techniques comprises of the following steps.

1. Data Collection: MRI images for AD detection were obtained from [5] and spiral drawings of patients were obtained from [6] to begin the suggested process. The data sets were broad and varied enough to include individuals with different illness stages and demographics, guaranteeing valid and trustworthy findings.
2. Data Preprocessing: To guarantee the precision of the deep learning models, the obtained data sets were preprocessed. Cleaning, normalising, and transforming the data sets were all part of the preprocessing that was done before the deep learning algorithms were applied.
3. Deep Learning Model Development: We created LSTM, DNN, CNN, and ANN that use patients' spiral drawings—a sensitive and non-invasive biomarker—for PD prediction. The AD prediction models comprised SVM, ANN, MobileNet, MobileNetV2, ResNet50, InceptionV3, VGG19, and VGG16. Each model was trained with the pre-processed data sets for maximum efficiency.
4. Performance Evaluation: The created models were then assessed for their efficacy and reliability in making AD and PD forecasts. The effectiveness of the models were measured by evaluation measures like accuracy, precision, recall, and F1 score. To guarantee the accuracy of the findings, cross-validation methods will be used.
5. Interpretation and Analysis: Finally, the evaluation findings were examined and analysed to shed light on how well the deep learning models performed in their ability to foresee Alzheimer's and Parkinson's.

The proposed framework for AD/PD diagnosis is depicted in Fig.1.

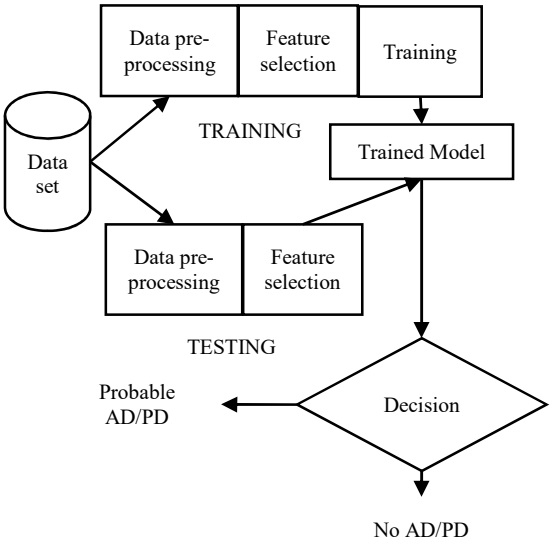


Fig. 1. Proposed framework for AD/PD detection

Initially, the AD and PD datasets were obtained, as is displayed in Fig. 1. To prepare the data for analysis, it was scaled, corrected, normalised, filtered, and smoothed. The dataset was then split in half for use in both training and testing purposes. A training dataset is used to teach a model. Model evaluation was performed on the test dataset. Fig.2 shows the hybrid model developed in this work.

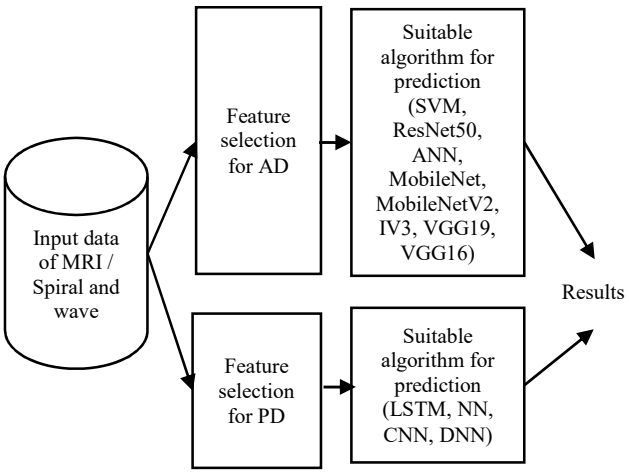


Fig. 2. Hybrid model for AD/PD prediction

As shown in Fig.2, the Input Dataset is Obtained, Model is Trained, Feature Selection for Alzheimer's is done, Suitable Algorithm such as CNN is applied, Feature Selection for Alzheimer's is done, Suitable Algorithm (LSTM, CNN, DNN, NN) is applied, and the results are predicted. Fig.3 shows the architecture of the proposed work.

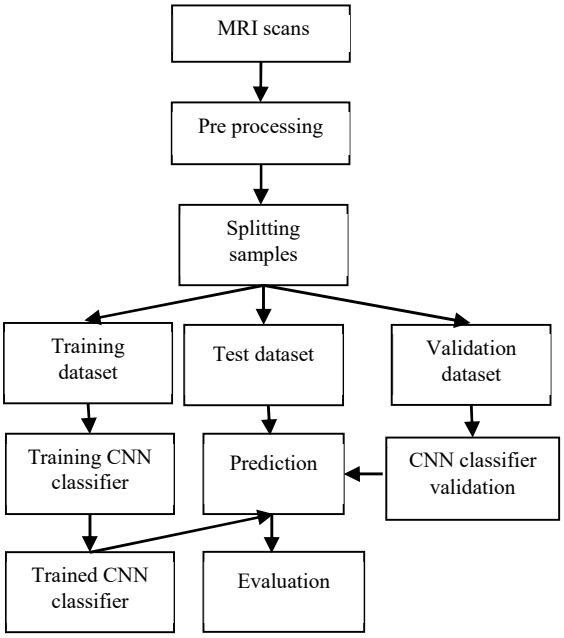


Fig. 3. Architecture of AD prediction

The three modules used in Fig.3 are explained below

i) Module 1:

In this module, the AD data was collected and trained using Deep learning Algorithms. Image data was imported from the drive and was read. The data images comprising of MRI scans were imported from the public repository. The dataset consisted of four classes of images both in testing and training set which were Very Mild Demented, Mild Demented, Moderate Demented, and Non-Demented. The training set consisted of 5121 Images while the testing set comprised of 1279 Images. The images were resized to 224x224 pixel size in dataset.

The PD dataset comprised of images and is pre-split into a training set and a testing set, consisting of spiral and wave images. The training set comprised of 144 Images while the testing set comprised of 60 Images. The images were resized to 224x224 pixel size in dataset.

ii) Module 2:

In this module, the data was extracted from the training folder and resampled. The dataset which was extracted from the train folder was classified into different Demented. The training dataset was used to fit the model. The validation dataset was used to validate the generalization ability of the model or for early stopping, during the training process. The testing dataset was used to for other purposes other than training and validating. The resampling techniques were then applied. Resampling is a methodology of economically using a data sample to improve the accuracy and quantity the uncertainty of a population parameter.

iii) Module 3:

In this module, transfer learning was performed on the pretrained model. Model wvaluation was performed using the performance metrics accuracy, loss, and F1-score.

The structure of the best performing VGG-16 model for AD detection is shown in Fig.4.

```
Model: "model_1"
_________________________________________________________________
 Layer (type)                 Output Shape              Param
=================================================================
 input_2 (InputLayer)         [(None, 176, 208, 3)]     0

 block1_conv1 (Conv2D)        (None, 176, 208, 64)      1792

 block1_conv2 (Conv2D)        (None, 176, 208, 64)      36928

 block1_pool (MaxPooling2D)   (None, 88, 104, 64)       0

 block2_conv1 (Conv2D)        (None, 88, 104, 128)      73856

 block2_conv2 (Conv2D)        (None, 88, 104, 128)      147584

 block2_pool (MaxPooling2D)   (None, 44, 52, 128)       0

 block3_conv1 (Conv2D)        (None, 44, 52, 256)       295168

 block3_conv2 (Conv2D)        (None, 44, 52, 256)       590080

 block3_conv3 (Conv2D)        (None, 44, 52, 256)       590080

 block3_pool (MaxPooling2D)   (None, 22, 26, 256)       0

 block4_conv1 (Conv2D)        (None, 22, 26, 512)       118016

 block4_conv2 (Conv2D)        (None, 22, 26, 512)       235980

 block4_conv3 (Conv2D)        (None, 22, 26, 512)       235980

 block4_pool (MaxPooling2D)   (None, 11, 13, 512)       0

 block5_conv1 (Conv2D)        (None, 11, 13, 512)       235980

 block5_conv2 (Conv2D)        (None, 11, 13, 512)       235980

 block5_conv3 (Conv2D)        (None, 11, 13, 512)       235980

 block5_pool (MaxPooling2D)   (None, 5, 6, 512)         0

 global_max_pooling2d_1 (Glo  (None, 512)               0
 balMaxPooling2D)

 flatten_1 (Flatten)          (None, 512)               0

 dense_2 (Dense)              (None, 1024)              525312

 dropout_1 (Dropout)          (None, 1024)              0

 dense_3 (Dense)              (None, 4)                 4100

=================================================================
Total params: 15,244,100
Trainable params: 15,244,100
Non-trainable params: 0
```

Fig. 4. VGG-16 model architecture for AD detection

Fig.5 shows the architecture of the CNN model for PD detection.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                 Output Shape              Param #
=================================================================
 conv1 (Conv2D)               (None, 128, 128, 128)     3328

 max_pooling2d (MaxPooling2D  (None, 40, 40, 128)       0
 )

 conv2 (Conv2D)               (None, 40, 40, 64)        204864

 max_pooling2d_1 (MaxPooling  (None, 12, 12, 64)        0
 2D)

 conv3 (Conv2D)               (None, 12, 12, 32)        18464

 max_pooling2d_2 (MaxPooling  (None, 4, 4, 32)          0
 2D)

 conv4 (Conv2D)               (None, 4, 4, 32)          9248

 max_pooling2d_3 (MaxPooling  (None, 1, 1, 32)          0
 2D)

 flatten (Flatten)            (None, 32)                0

 dropout (Dropout)            (None, 32)                0

 fc1 (Dense)                  (None, 64)                2112

 dropout_1 (Dropout)          (None, 64)                0

 fc3 (Dense)                  (None, 2)                 130

=================================================================
Total params: 238,146
Trainable params: 238,146
Non-trainable params: 0
_________________________________________________________________
```

Fig. 5. CNN model architecture for PD detection

IV. Experimental Setup and Results

Experiments were carried out with the following system specifications: 1 x B550 Chipset based Motherboard, 1 x Ryzen9 5900X: 12 Cores & 24 Threads & 3.7GHz to 4.8GHz, 2 x 32GB DDR4 3200 With Heatsink (64GB), 1 x 500GB NVMe SSD / M.2, 1 x 2TB NAS SATA HDD for STORAGE, 1 x GeForce RTX 3050 8GB graphics card, 1 x ATX/Mid-

Tower Chassis (with 1+3 Fans), 1 x 750W Power Supply Unit with 80+, 1 x Liquid Cooling System, 1 x 24" Full HD Monitor, 1 x USB Keyboard & Mouse, 1 x Ubuntu Linux OS (Desktop Version - 18.04).

Mongo DB was used for the storage off the Data Set. A web based application was built using HTML, CSS, JavaScript. Python was used for coding the ML and DL algorithms.

A. Experimental results for AD detection

The SVM model achieved a low accuracy of 19% on the AD dataset. Table I shows the SVM confusion matrix for AD diagnosis.

TABLE I. SVM CONFUSION MATRIX FOR AD DIAGNOSIS

		Predicted classes			
		ND	**VMD**	**MD**	**MdD**
Actual Classes	**ND**	32	0	53	94
	VMD	0	0	0	0
	MD	0	0	0	0
	MdD	0	2	5	5

As can be observed from table 2, 32 records were correctly classified as belonging to ND class while 53 and 94 records belonging to ND class were misclassified as belonging to MD and MdD class respectively. Likewise, 5 records were correctly classified into MdD class. However, 2 records and 5 records belonging to the MdD class were misclassified as belonging to the VMD and MD classes respectively. Fig.6 depicts accuracy and loss plots of the ANN model for AD prediction.

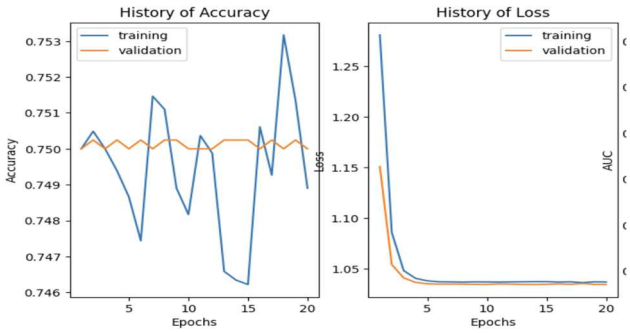


Fig. 6. Accuracy and loss plots of ANN model for AD detection

The ANN model achieved an accuracy of 75% at epoch 18 and validation loss of 0.88. The MobileNet model achieved an accuracy of 75% as depicted in Fig.7.

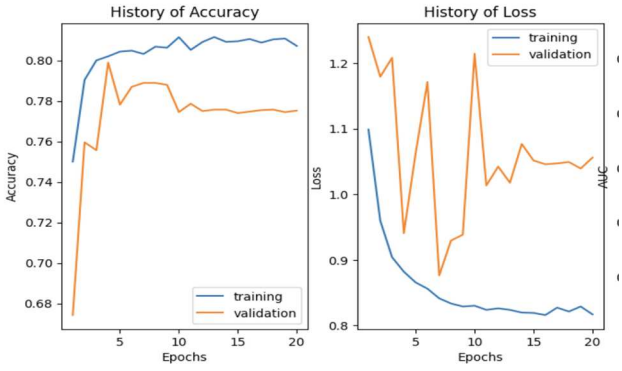


Fig. 7. Accuracy and loss plots of MobileNet model for AD detection

The MobileNetV2 model achieved an accuracy of 78.12%. Fig.8 depicts the accuracy and loss plots of the MobileNet V2 model for AD prediction.

Fig. 8. Accuracy and loss plots of MobileNetV2 model for AD detection

The ResNet50 model achieved a lower accuracy of 55.17% as shown by the accuracy and loss plots on the AD dataset.

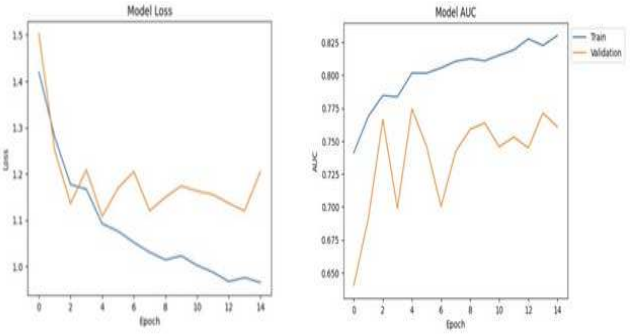


Fig. 9. Accuracy and loss plots of ResNet50 model for AD detection

The InceptionV3 model achieved an accuracy of 85% as shown in Fig.10.

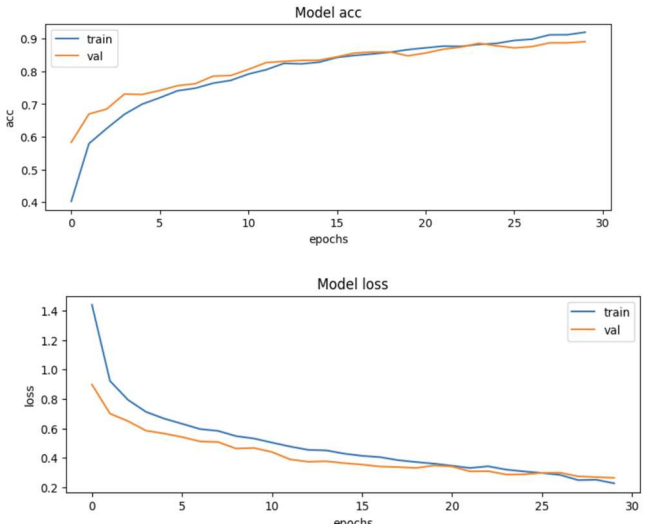


Fig. 10. Accuracy and loss plots of Inception V3 model for AD detection

The VGG19 model achieved an accuracy of 88% as shown in Fig.11.

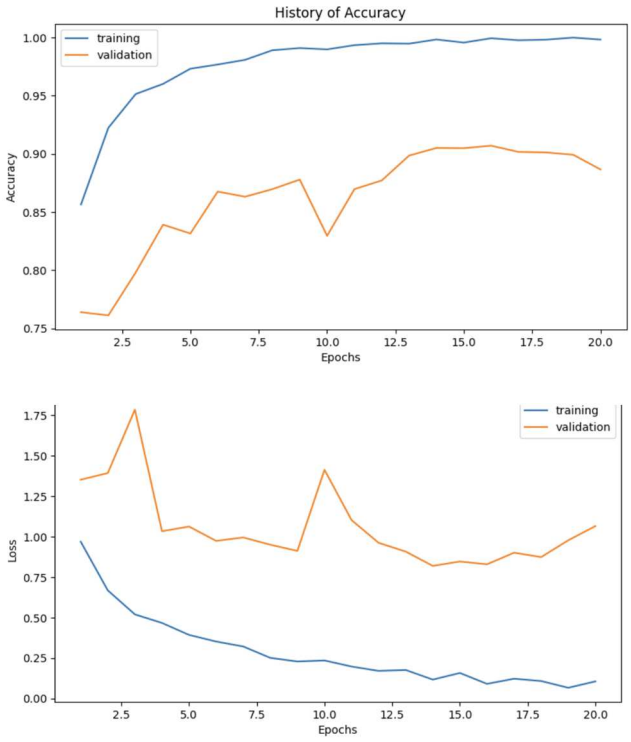


Fig. 11. Accuracy and loss plots of VGG-19 model for AD detection

The VGG16 model achieved the highest accuracy of 99.36% as shown in Fig.12.

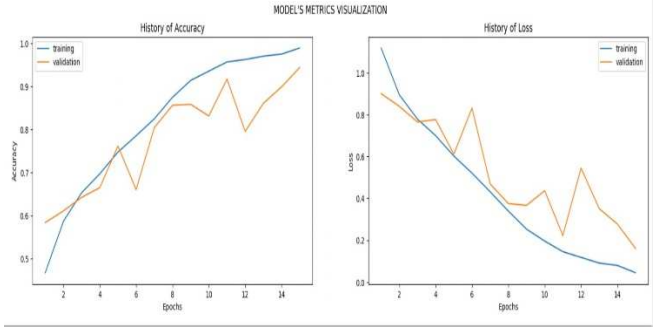


Fig. 12. Accuracy and loss plots of VGG-16 model for AD detection

Fig.13 shows the comparison of the models in terms of accuracy for AD detection.

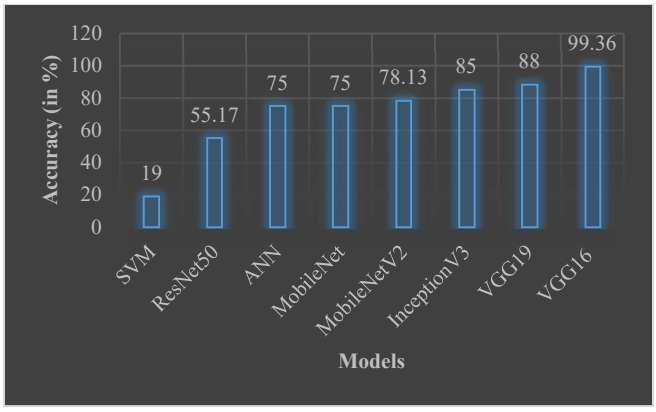


Fig. 13. Accuracy comparison of models for AD detection

As can be observed from Fig.13, the VGG-16 model performed with accuracy improvements ranging from 11.36% to 80.36%.

B. Experimental results for PD detection

The CNN Model achieved an accuracy of 96.85% as shown in Fig.14.

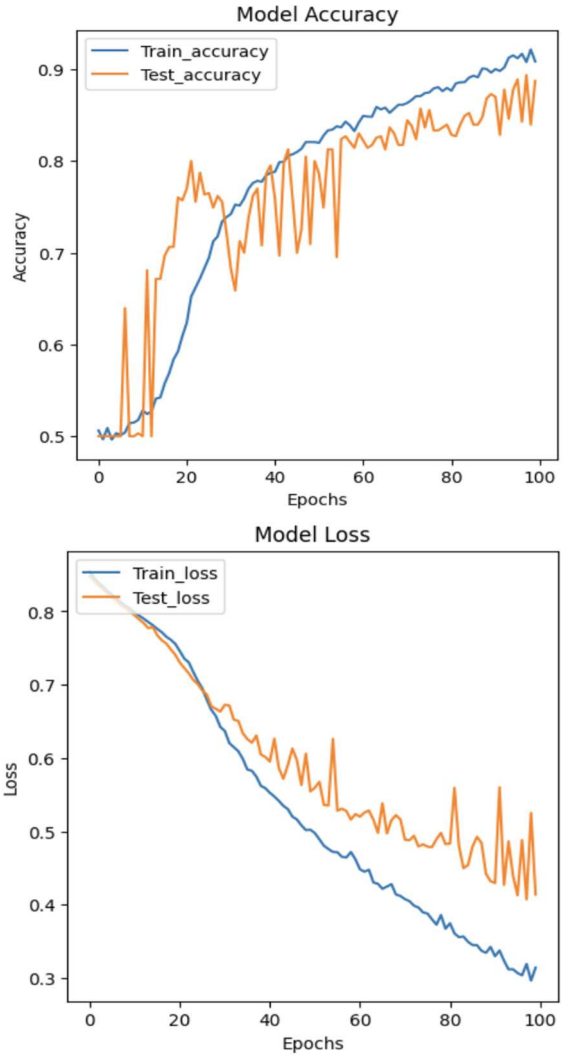
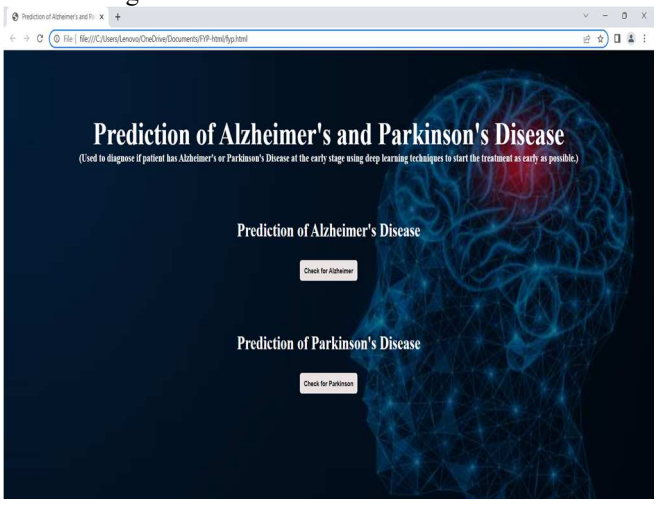


Fig. 14. Accuracy and loss plots of CNN model for PD detection

Fig.15 shows the integrated front end of our web application for detecting AD and PD.



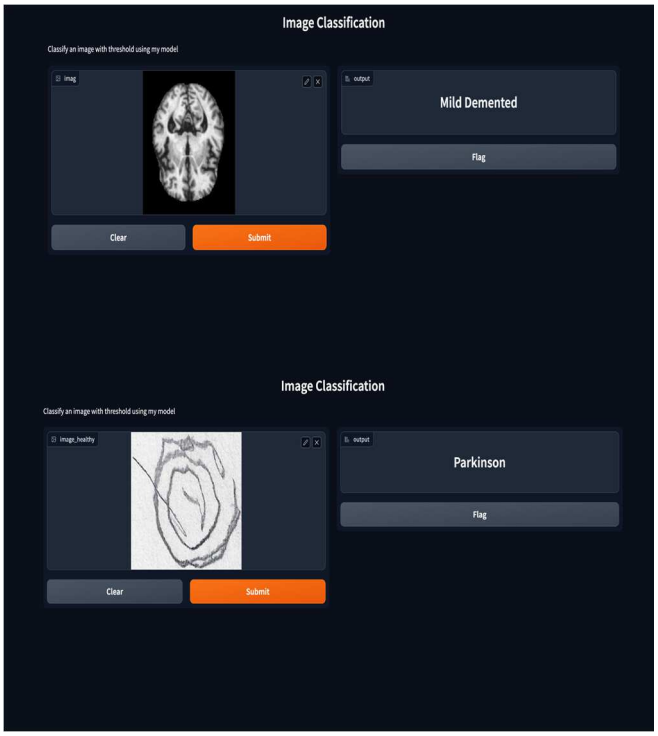


Fig. 15. Integrated front end of web application for AD/PD detection

V. Conclusion and Future Scope

This research highlights the potential of deep learning techniques for predicting neurodegenerative diseases like Alzheimer's and Parkinson's disease. The study demonstrates the effectiveness of using MRI scans and spiral drawings as non-invasive biomarkers for accurate disease diagnosis. The use of CNN algorithms for Parkinson's disease prediction and VGG16 for Alzheimer's disease prediction shows promising results for early detection and intervention, leading to better patient outcomes and improved quality of life. The limitations of this research include the relatively small dataset size used for training and testing the deep learning models, which may affect the generalizability of the findings. The focus on specific imaging modalities and biomarkers for AD and PD detection limits the applicability to other diagnostic methods. External validation using independent datasets would enhance the reliability of the results

Future research can explore the use of more advanced deep learning techniques and other non-invasive biomarkers for disease diagnosis. The use of multi-modal imaging data, such as combining MRI scans with other medical data, can provide more accurate and reliable predictions. Additionally, the development of more personalized models that take into account individual patient characteristics and medical histories can further improve the accuracy of disease prediction. In conclusion, this research paves the way for further investigation into the use of deep learning-based diagnosis and treatment of neurodegenerative diseases, with the potential to significantly improve healthcare outcomes and quality of life for affected individuals.

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