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Original Article

Opti-MuDR_CNN: An Enhanced Approach for Classification of Early Onset of Alzheimer's Disease

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Abstract - *Alzheimer's Disease (AD) is commonly found in aged people and adults. This kind of disease is predicted using various hybrid methods, such as a combination of Machine Learning (ML) and Deep Learning (DL) in the medical field. Therefore, image classification problems are considered a significant limitation of the existing research and the current scenario. In Current research, a novel technique - Opti Multi Hidden Deep rooted Convolutional Neural Network has been utilized to classify the early onset of AD. In our work, we have given the segmented images to different architectures like EfficientnetB7, Restnet50, and Opti Multi hidden deep-rooted CNN, where our proposed model Opti Multi hidden Deep rooted CNN model has achieved the best accuracy. The proposed method Opti Multi Hidden Deep rooted Convolutional Neural Network has been compared in terms of certain performance measures like MAP - Mean-Average-Precision, F1-score, recall, precision, and accuracy with the existing methods like ResNet50 and EfficientNetB7 and obtained the best results than existing methods. Eventually, the proposed approach achieved more efficient results compared to the other existing methods. In the future, large real-time datasets will be used with the integration of the proposed system to enhance accuracy and sensitivity.*

Keywords - *Alzheimer's Disease (AD), MRI, Convolutional Neural Network (CNN), Dwarf Mongoose Optimization Algorithm (DMOA), Deep Learning (DL).*

1. Introduction

In the human body, the brain is considered a complex function and structure; obtaining information from a single modality, however not provide adequate feature data for diagnosis. Recently, with the help of neuroimaging technology development, multimodal information can be gathered in different examinations of the fields of study, enabling a data source for AD diagnosis. Further, various modality information can provide data about the brain data from various perspectives. For instance, structural MRI imparts data corresponding to brain tissue categories, while PET evaluates the rate of glucose brain metabolic [23]. AD is considered a chronic neurodegenerative disorder along with a relentless improvement that impacts a person's cognitive capabilities and memory functions [25]. Basically, AD pathogens are induced because of the tau hyper-phosphorylation protein [27] and amyloid-βeta - Aβ [29] overproduction. According to the existing research, dementia is studied the 6th deadly illness in the United States. In the year 2015, approximately 47.47 million people globally were predicted to have the disease dementia, which also includes Alzheimer's Disease (AD). Therefore, it is anticipated to reach 50 - 152 million by 2050. Further, AD interfaces with various situations of human life consisting of psychological, physical, economic, and social aspects that develop a massive economic burden. Therefore, the dementia cost of global socioeconomic found 2015 reached around 818 billion. AD development is estimated to increase from 60% to 80% of people [24] [30]. AD is widely recognized as the most common age-related neurodegenerative condition found in elderly individuals, with around 50% - 75% impacting approximately 23 – 35 million individuals globally. Alzheimer's disease is divided into late-onset and early-onset groups based on age, a significant biological risk factor. At the same time, the AD neuropathologic and clinical features of dementia have a higher possibility of misdiagnosis with a percentage of 17-30 [1]. This field concentrated on various neuro-economic examinations that enabled reliable recommendations regarding the impact of an early diagnosis of AD. Specifically, in the patient management section, symptomatic intervention and timely detection of AD is cost-effective due to the limited efficacy [6] [16]. However, the main reason for AD is still not found, and in rare cases, it is presumed to be a genetic problem [2] [20]. This kind of disease typically affects old adults worldwide and follows these biological pathways that include cell-membrane processes, immune system, and lipid metabolism. At the same time, the AD features overlap with the neuropathologic, clinical, and other neurodegenerative dementia forms, resulting in misdiagnosis [19]. Moreover, the existing research varies from the present predicting future AD onset in the subsequent ways: At the initial stage, the existing prediction method was in accordance with the collection of data while the patients were cognitively in good health. Next, mainly concentrated on variables

executed in the screening stage evaluate predictive performance and early-intervention trial utilizing linguistic metrics acquired from a single administration. Various ML-based methods [26], [28] are used to handle a depiction of linguistic performance. Eventually, the prediction methods are compared with the features taken from traditional variables connected with the prediction of AD, which is a higher risk [4]. Furthermore, clustering methods are considered in the existing research, which is considered an efficient ML tool for identifying the structure of the dataset.

Healthcare employs supervised and unsupervised approaches to analyze patterns and structures in labeled or unlabeled datasets. Unsupervised methods are efficient for datasets without known outcomes. The research mainly concentrated on clustering-based methods employing neurological disease datasets that focused more on AD. Therefore, these are considered more appropriate for segregating AD patients from the list based on their similarities. The clustering algorithms are capable of identifying complex patterns to predict disease [5].

In recent years, various ML techniques, including ensemble methods, SVM-support vector machine [22], NN - Neural Networks [3] and KNN - K-nearest neighbor have been utilized in AD classification. Periodically, the classification occurred by a specific classifier does not give the expected outcome because of particular factors. This process will increase the usage of multistage and ensemble classifiers for appropriate classification outcomes.

Normally, the ensemble techniques utilize a voting method primarily, and the multistage classifier utilizes the outcome of one stage-classifier given as input to the next level classifier. Thereby, the benefits of individual classifiers can be merged to solve certain disadvantages [8]. In the current research, the patients affected by AD are identified, and this research mainly concentrates on predicting the Alzheimer's patients' count with a novel method that helps to solve the issues that persist due to image classification and increases the higher chance of AD prediction at an early stage.

The AD dataset has been gathered from the public domain with the images including AD - 4360, CN - 4175, and MCI - 4247 images with specific parameters that include T2 weight type, T2 weight, and modality - MRI [7]. The T2 weight type includes AX_T2_STAR, FSE PD/T2, Axial field with Mapping zero angle, Sagittal 3D FLAIR, and Field Mapping. Further, in this research, we have used Gray_scale conversion, erosion, ROI, and CLACHE preprocessing approaches by reading the provided input.

Therefore, Opti Multi-Hidden Deep rooted Convolutional Neural Network has been utilized for the classification of early onset of Alzheimer's Disease. The addition of variants and CNN [21] has been used during the experimentation process with the performance evaluation, which helps to identify the effectiveness of the proposed method. Eventually, the proposed Opti Multi-Hidden Deep rooted Convolutional Neural Network has been compared with the existing methods ResNet50 and EfficientNetB7 on certain performance metrics such as accuracy (acc), precision (pre), recall (re), F1-score (F1sc), and MAP - Mean Average Precision. The various sections included in the currently proposed research are as follows: Section 2 explains the existing technique related to the recommended study, and each technique's benefits and drawbacks in predicting AD will be explained. Section 3 defines the methodology of the research study with the proposed Opti Multi-Hidden Deep rooted CNN for the classification of the early onset of AD.

Section 4 explains the results of the proposed methodology, with the significant observations from the results will be discussed with a comparison to the existing approach. Section 5 explains the research study's outcomes, and the suggested framework's importance in the future study will be provided. The major contributions of the proposed approach by addressing the research gaps of existing methods are as follows:

- Opti-MuDR_CNN utilizes a sophisticated approach, a multi-resolution analysis, and dynamic receptive fields to enhance feature learning.
- This allows it to extract more useful features from brain images. The proposed model exhibits heightened sensitivity in identifying initial indications of AD due to improved feature representation and training procedures. Opti-MuDR_CNN employs data augmentation approaches to tackle data imbalance, resulting in enhanced performance applicable across various phases of AD.

2. Literature Survey

Extensive study has been conducted on the identification of AD, which involves several challenges. In this [31] study, the researchers utilized a sparse autoencoder and 3D convolutional neural networks. A unique algorithm was developed to determine the medical state of an individual by analyzing an MRI scan of their brain. The primary advancement was the integration of 3D convolutions, leading to superior performance in comparison to 2D convolutions. The convolutional layer was pre-trained using an auto-encoder; however, it was not fine-tuned. Based on the forecast, performance is anticipated to improve via the process of fine-tuning. In their study, the scientists presented a classification technique for AD utilizing RNNs [21].

CNN was first developed to get insights into the spatial characteristics of MR images for the aim of classifying them. The RNN and cascaded Bidirectional Gated Recurrent Unit (BGRU) layers were designed to make use of CNN outputs at different time intervals to identify and isolate longitudinal characteristics for Alzheimer's disease categorization. Rather than extracting characteristics individually, it is advised to learn spatial and longitudinal properties jointly to optimize performance. Researchers in [32] introduced a novel approach to summarising existing methods for automatically detecting

dementia. Their method focuses on the real viewpoint and patterns in categorization. The voxel, RoI-based, and vertex group classification techniques include the Bayes classifier, SVM, ANN, and Linear Discriminant Analysis (LDA). The conclusive implementation of these classifiers demonstrated the existence of several methods for differentiating AD from Head Circumference (HC) beyond only considering accuracy.

The outcome indicates that the model achieved a greater level of accuracy, around 91.33%, when comparing individuals with AD to those without cognitive impairment (NC). Similarly, when comparing individuals with pMCI to those with sMCI, the accuracy was approximately 71.71%.The authors of the paper [10] utilized Next-Generation Sequencing (NGS) technology to examine both familial and de novo instances of EOAD (Early onset of Alzheimer's Disease). The researchers utilized a 50-gene panel that consisted of well-established causative and potentially detrimental variants associated with several neurodegenerative disorders, such as AD. The study group consisted of 67 individuals who were affected by EOAD. Genetic analysis was conducted to find any abnormalities within the specific gene panel that was chosen. Alickovic et al. [33] introduced a system that uses machine learning algorithms to detect AD. Histograms are utilized to convert images into features that contain relevant brain characteristics in the first phase. Subsequently, machine learning approaches are employed to classify and diagnose AD.

The experimental findings demonstrate that the RF classifier effectively differentiates between AD patients and control participants. Contemporary CAD systems include machine learning as a computational method for examining trends in medical data. The CAD system utilizes many machine-learning techniques, including regression, classification, and clustering. The utilization of a machine learning technique yields superior accuracy in classifying data by leveraging the extracted features from images. Brain MRI scans utilize both single modalities and multimodalities as features to detect structural and textural changes [34]. In [35], authors show that it is possible to achieve comparable performance. Both the residual network and simple 3D CNN designs demonstrated a high level of complexity and depth when applied to 3D structural MRI brain data. Conventional machine learning methods usually need human identification of predetermined brain areas of interest (ROIs) using known MRI characteristics of AD.

Due to the current lack of knowledge on definite MRI biomarkers for AD, probably, pre-selected Regions of Interest (ROIs) cannot encompass all the potentially valuable information needed to comprehend the intricacies of AD fully. Manual selection is susceptible to subjective mistakes and can be a time-consuming and labor-intensive process[36]. [37] introduced a unique Convolutional Neural Network (CNN) framework that utilizes a multimodal MRI analytical approach using either fMRI or DTI data.

The framework categorized individuals into three groups: those with AD, those with NC, and those with aMCI. While the current model obtained a good level of accuracy in classification, it is anticipated that replacing the 2D convolution with 3D convolution will result in improved performance. This study aims to understand the genetics of EOAD, a subtype of AD that developed before 65The researchers utilized Next-Generation Sequencing (NGS) to genetically analyze a cohort of individuals with EOAD from Thailand with great coverage.They targeted 50 genes linked to AD and other neurodegenerative illnesses, suggesting a hereditary link. The study found remarkable findings with implications beyond EOADA new mutation, APP p.V604M, and a causal variation has been identified, emphasizing the need for genetic testing in understanding EOAD heritability. Neurodegenerative diseases are genetically complicated, as 61 missense variations were found across 21 genes. Dementia and neuronal degeneration have been associated with six potential pathogenic variants, which include LRRK2 p.R1628P, CSF1R, MAPT P513A, p.P54Q, p.L536V, and TREM2 p.L211P. The literature offers valuable insights into the utilization of ML algorithms and genetic analysis techniques for the identification and comprehension of AD. However, it is crucial to acknowledge various limitations and identify areas that require further enhancement:

- Several of the studies mentioned employed small groups of participants, which restricts the capacity to apply the findings to a wider range of situations and may not completely encompass the genetic diversity found in other populations.
- Data imbalance refers to datasets that have an unequal distribution of samples, particularly with fewer examples from the early stages of AD. Unequal accuracy and applicability of models can cause bias in their performance and generalization.
- Numerous current techniques for AD classification depend on manually designed features, which might not fully reflect the intricate nature of AD-related alterations in brain imaging. Certain current approaches may exhibit insufficient discernment in recognizing the early stages of AD or minor alterations in brain structure and function.

3. Research Methodology

The image classification problems are considered a major limitation in the existing research. In the current scenario, Opti Multi-Hidden Deep Rooted Convolutional Neural Network has been utilized for classifying EOAD. Here, the proposed novel method has been used to determine the AD with the symptoms and in accordance with the brain MRI utilizing improved deep learning methods. Moreover, the Opti Multi-Hidden Deep rooted Convolutional Neural Network has been compared with the significant factors that include MAP - Mean-Average-Precision, F1-score, recall, precision, and accuracy. Therefore, the proposed approach has been evaluated against conventional methods such as ResNet50 and EfficientNetB.

Table 1. Review of literature

Reference No.	Year	Methodology Used	Advantages	Limitations and Future Direction
[9]	2020	Voice analysis and automatic speech methods are utilized to monitor patients suffering from AD. Further, it also reviews 90 papers that denote existing research that concentrated on the classification and feature extraction methods.	The existing diagnostic methods and treatments enhance the patients' lifespan and continue the rational health systems efficiently.	The main limitation of the existing research is due to the lack of knowledge about AD.
[10]	2019	Genetic-analysis of early-onset AD utilizing sequencing of next-generation.	The tool utilized in the research to visualize biological networks that are non-redundant with larger gene clusters that were connected into functional networks processed by statistical estimation with the Gene ontology of existing annotations.	The main drawback of the work was due to a lack of functional assessment in pathogenic variants. Further, another problem was that the research could not be done on copy-number variants for validating the mutation segregation.
[12]	2020	This paper utilized coexpression network analysis and quantitative mass spectrometry in order to execute the largest study on AD.	This study uses samples of 400 cerebrospinal fluid and more than 2000 brains analyzed by quantitative proteomics. This process has been executed in order to predict the biological processes and proteins in AD.	The performance of cell-type regression was performed before the analysis of the network obtained from the pooled samples. Here, the protein network represented was not directly comparable to the existing network. Nevertheless, proteins presented in the research overlap with the appropriate set, and these were achieved after regression of cell type was expressed in a different way in AD.
[13]	2019	In this research, an unconventional method has been utilized that consists of an AD proxy pheno-type to raise the size of the sample and, here, used gained-novel biological knowledge and nine-novel loci on AD- etiology.	Strong genetic correlations are exhibited with various results of health-related queries. Further, Mendelian randomization outcomes imply a protective impact of AD risk cognitive ability.	The sample used in the research is late-stage; severe AD cases vary from supernormal cases. Due to this reason, the identification of polygenic has a higher result compared to the population samples.
[14]	2022	DenseNet-121 architecture's convolution layers are substituted with depth-wise convolution layers in this work.	When compared to the other existing frameworks, this model provided an efficient outcome and obtained a convincing performance rate.	Still, the method's performance should be enhanced by using different modifications that include a genetic algorithm to select important components from feature maps. Further, future work should be concentrated on layer-wise modification and comparison to achieve an efficient AD classification model.
[15]	2020	This research focused on the advanced studies executed on MRI brain classification and brain structure in order to predict AD. Further, this study discussed the functioning of brain-	Different issues are identified, and proper segmentation techniques are utilized with different complexity. Therefore, these techniques' outcomes have been proven	Segmenting Brain MRI is a difficult process due to the presence of noise, low contrast, and partial volume impact. Moreover, the AD automatic classification is challenging

		structure segmentation and how it enhances AD performance classification.	with accurate results. In most of the scenarios, DL methods are used for classification and brain structure segmentation, and it has acquired more attention because it can provide efficient outcomes over large-scale data.	because the MRI anatomical structures are low-contrast.
[17]	2019	The main focus of the work was to generate a CABD - computer-aided brain-diagnosis system to identify AD symptoms through the scan. Normally, this method uses MRI for classification purposes with various feature-extraction methods. Normally, MRI is considered a non-invasive system, broadly used in medical fields to Identify cognitive abnormalities.	A comparative analysis has been conducted by experimenting with the feature extraction method. The findings provided efficient results and concluded that ST - Shearlet Transform, a feature extraction method, provides enhanced outcomes for AD.	In the future, other classification methods that include AdaBoost, RF - Random Forest, SVM, and neural networks should be implemented to find out the CABD systems improvement. Further, appropriate DL - methods should be utilized to enhance classification accuracy.
[18]	2020	This study aimed to classify dementia stages using the SCNN, a Siamese convolutional neural network based on VGG-16 architecture.	The experimental results executed on publicly available datasets obtained 99.05% accuracy for the dementia stages classification. The performance of these models was compared with existing methods, and this technique proved to be superior in terms of accuracy.	In the future, the utilized model should be examined and processed on other computer-aided-diagnostic issues. Also, the investigation should occur on training data enhancement for classification.

3.1. Data Collection and Preprocessing

Data collection plays an essential role in the experimentation process, which is the initial factor that should be followed in every research. Here, the dataset used for the experimentation process has been gathered from the ADNI - AD Neuroimaging Initiative for the research. This is considered a multisite examination that focuses on enhancing clinical trials in order to provide appropriate treatment or prevent AD. This current cooperative examination incorporates funding and expertise received from the public and private sectors to examine the AD subjects. Researchers started the AD progression at 63 sites to track the details in countries like Canada and the US with genetic-biological markers, biochemical, and neuroimaging.

The information from this site helps to identify efficient clinical trials for AD treatment and prevention. The data used in the experimentation process is as follows: The AD dataset has been gathered from the public domain with the images including AD - 4360, CN - 4175, and MCI - 4247 images with specific parameters that include T2 weight type, T2 weight, and modality - MRI. Further, the MIPAV -Medical_Image_Processing_analysis_and_Visuali -zation application uses quantitative visualization and analysis of the images collected from various modalities such as PET, microscopy, CT, and MRI in the medical field.

Furthermore, in the preprocessing stage, the input that is taken from the public domain has been experimented with specific parameters to execute the research and employ the proposed novel method. This process is considered a significant portion of the study for accurate results. The inappropriate data has been filtered from the provided input data. The uncertainties that include unwanted data and noise that impact the classification accuracy during the process have been removed. This stage helps to scan the collected images and uses certain preprocessing methods, including CLACHE, ROI, Erosion, and Gray_scale conversion. CLACHE (Contrast Limited Adaptive Histogram Equalization) has been used to improve the histogram equalization to obtain the optimum output to predict AD with the available datasets. The quality of the image will be adjusted by modifying certain pixels on the histogram of the image. ROI - Region_of_Interest is usually identified in a medical image taken from the available datasets; these functions can be utilized either for ROI bounding in both single or multiple. Erosion is a morphological operation performed with various advantages, including image-feature dimension and eroding the boundary objects. Hence, this method is used to minimize the object thickness to reduce the white region. Finally, the gray-scale conversion plays a significant role in the preprocessing stage for storing the available data (images) in a single black-and-white array that requires an evaluation of a single convolution.

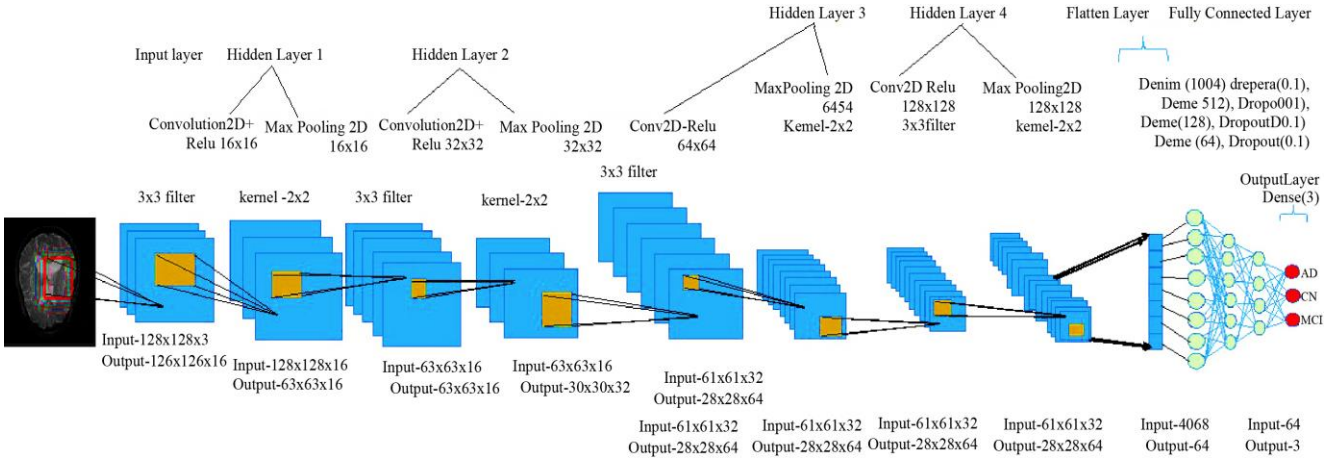


Fig. 1 The architecture of the proposed method

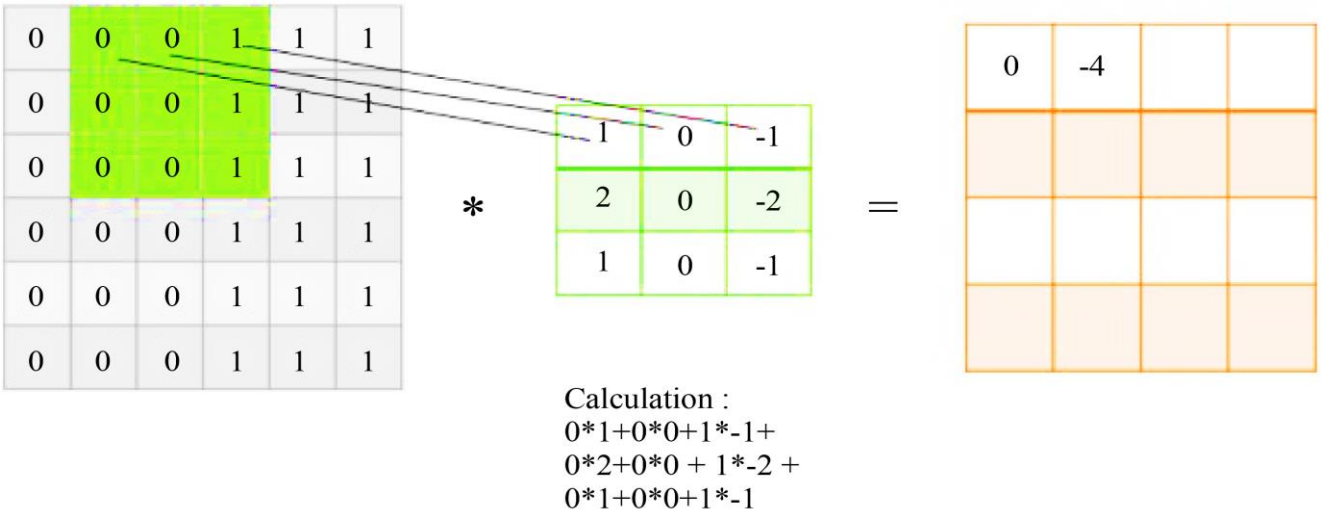


Fig. 2 Matrix multiplication workflow between filter and image

3.2. Feature Extraction

The feature extraction techniques are used for image extraction in the proposed method. Here, the GLCM - Gray Level co-occurrence Matrix textured feature has been used with the neighboring co-occurrence-gray-level evaluation with the ROI square matrix dimension with the gray levels represented in the MRI images. The features used in the research include standard_deviation (std), mean (mean), ma (glcm_mx), homogeneity (homo), dissimilarity (diss), contrast (cont), entropy (ent), and energy (ene). The GLCM features have been represented as Variance, Prominence, shade, correlation, inertia, homogeneity, entropy, and energy.

3.3. Proposed Opti Multi-Hidden rooted CNN

The Opti-MuDR_CNN method for analyzing EOAD is an improvement over the existing methodology. It uses Multi-Dimensional Representation (MuDR) to capture complex patterns, resulting in better classification accuracy. Opti- MuDR_CNN also integrates adaptive optimization techniques and a pixel-level analysis module. This module identifies small structural modifications that traditional approaches miss, improving diagnosis accuracy and sensitivity. Our approach shows significant potential for early detection and tracking of EOAD.The classification process was performed once the feature extraction method was compared with the Opti MultiHidden Deep-rooted CNN method. Here, the CNN architecture has been modified with the maximum number of hidden layers. Therefore, four hidden layers were utilized in the research to learn the model in an effective way than existing CNN methods. The architecture of the proposed method is represented in Figure 1.

Algorithm: Proposed Opti Multi-Hidden rooted CNN
Input: Training dataset (X_train, y_train), Testing dataset (X_test, y_test)
Output: Classification of AD

1. Initialization: 4 hidden layers Input layer: 128 x 128 x 3 Filters: 3x3
2. Feature Extraction: Pass the input image through the input layer. ReLU (to introduce nonlinearity)
3. Hidden layer 1: Output of the input layer to the 1st hidden layer. Perform Max-Pooling: 2x2 kernel size.
4. Hidden Layer 2: Conv2D (to extract features) ReLU
   Perform Max-Pooling: 2x2 kernel size
5. Hidden Layer 3:: Conv2D
   ReLU
   Perform Max-Pooling: 2x2 kernel size

6. Hidden Layer 4:: Conv2D
   ReLU Perform Max-Pooling:
   2x2 kernel size
7. Fully Connected Layers: Flatten the features to a 1D vector Pass through 4 Dense layers with ReLU activation and 4 dropout layers to minimize overfitting. The final output size of the fully connected layer is (None, 64).
8. Output Layer: softmax activation

3.3.1. Input Layer

The input image considered in the study was 128 x 128 x 3 passed into the input layer, and these layers employed matrix multiplication with the filters consisting of 3 x 3, denoted in Figure 2. Moreover, the filter passes to the entire image during the acquirement of the feature map; hence feature map includes sharp edges, textures, curves, and much more. Once the feature map had been obtained, a ReLU rectified-linear AF activation function was employed by introducing the concept of nonlinearity; this AF is nothing but a piecewise linear function or non-linear function that helps to obtain output directly from the input if it is a positive value; otherwise, the output is zero. The mathematical expression of ReLU has been denoted below:

$$F(x1) = \max(0, x1) \quad (1)$$

x1 - positive values. During the activation of the Neurons layer using the AF and the generated feature maps with the provided respective count of presented neurons. *Here.,* We have utilized 16 neurons; therefore, the input layer was provided with the image size 126 x 126 x 16.

3.3.2. Hidden Layer 1

In Hidden Layer 1, the input layer with the output was passed into the 1st hidden layers. After this, max-pooling was performed to provide the acquired image with less dimension to retain the vital information. In the current study, we used a 2 x 2 kernel size with the maximum values, and the input size was denoted as 126 x 126 x 126 was minimized to 63 x 63 x 16.

3.3.3. Hidden Layer 2 - Cov2D and Max Pooling Layer

In Hidden Layer 2, the convolutional layer has been utilized to extract the features from the provided input image with the Feature map1 taken from the hidden layer1. After, this has been passed into the con2d layer with the fixed filter size denoted as 3 x 3 with ReLU AF. Therefore, the output procured in the convolutional layer from the provided input size is denoted as 63 x 63 x 16 x - 61 x 61 x 32. Next, the output procured from con2d was passed to the Maxpooling layer along with the fixed kernel size 2x2. Eventually, the size of the image was minimized with the utilization of the max-pooling layer and the outside of the hidden layer 2 was denoted as 30 x 30 x 32.

3.3.4. Hidden Layer 3 - Cov2D and Max Pooling Layer

In Hidden Layer 3, the convolutional layer has been utilized to extract the input image features using the feature map2 taken from the hidden layer 2. After, this has been passed into the con2d layer with the fixed filter size denoted as 3 x 3 with ReLU AF. Therefore, the output procured in the convolutional layer from the provided input size is denoted as 30 x 30 x 32 x - 28 x 28 x 64.

Next, the output procured from con2d was passed to the Maxpooling layer along with the fixed kernel size 2x2. Eventually, the size of the image was minimized with the utilization of the max-pooling layer and the outside of the hidden layer 2 was denoted as 14 x 14 x 64.

3.3.5. Hidden Layer 4 - Cov2D and Max Pooling Layer

In Hidden Layer 4, the convolutional layer has been utilized to extract the features from the provided input image with the Feature map3 taken from the hidden layer3. After, this has been passed into the con2d layer with the fixed filter size denoted as 3 x 3 with ReLU AF. Therefore, the output procured in the convolutional layer from the provided input size is denoted as 14 x 14 x 64 x - 12 x 12 x 128.

Next, the output procured from con2d was passed to the Maxpooling layer along with the fixed kernel size 2x2. Eventually, the size of the image was minimized with the utilization of the max-pooling layer and the outside of the hidden layer 2 was denoted as 6 x 6 x 128.

3.3.6. Fully Connected Layers

Once the features have been extracted from the images, they are next inputted into the fully linked layers that utilize 4-Dense layers, 1-Flattern layer with Relu AF, and 4-dropout layers. Further, the flatten was employed to layer with input shapes represented as (6, 6, 128), then the layer output was denoted as shape (none, 4608).

The dense layer was grouped with the features in the specified neurons, including Dense (1024), that converted the 4608 to 1024 neurons. Each dense layer was performed in the process; nevertheless, dropout layers are located in the middle of each dense layer, and these layers typically help to minimize the model overfitting issues. Eventually, the final size of the fully connected layer was denoted as (None,64).

3.3.7. Output Layer

In the output layer, three classes are identified from the Dense layer with the softmax AF that is used to find the probability function. Therefore, this can be obtained by calculating the exponent value for every part and dividing by the exponent values sum represented as below:

$$\text{Probability}(x) = \exp(\text{value v1}) / \text{sum v1 in list } \exp(v) \quad (2)$$

3.3.8. Bias

In the current study, the bias concept has been utilized for shifting AF towards the right or left with the comparison of the y-intercept represented in the line equation. Therefore, the bias values are used in each convolution neuron with the constant value zero has been represented in Figure 3. This value will be decided whether the provided neuron is activated or not.

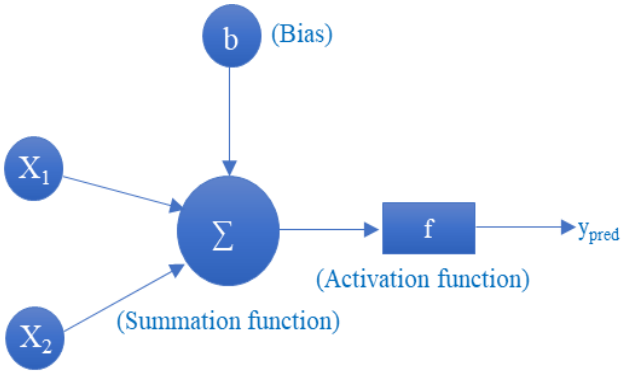


Fig. 3 Bias concept with summation and activation function

3.3.9. Adam Optimization (AO)

The Adam optimization has been utilized in the research with a learning rate of 0.0001.

Optimization (Adam learning_rate = 0.0001));

This technique is basically derived from the estimation of the adaptive moment, and this optimization method is the stochastic-gradient-descent extension employed to modify the network weights while undergoing the training procedure. Contrary to a single-learning rate via training in SGD, AO upgrades the network learning rate with the weight individually. The AO development has various benefits of RMSPropo and AdaGrad algorithms. Therefore, most of the features of AO are inherited from RMSpropo and AdaGrad algorithms.

3.3.10. Opti-MultiHidden Deep-rooted CNN Model

The main cause of using an Opti Multi-hidden deep-rooted CNN model in the hidden layers is that it generally maximizes the image's extraction processes with the deep features to maximize the model's accuracy. Therefore, this model produces the effective root in the accurate class identification with the feature map extraction from the provided input (image) to featuremmap1 -> featuremap2 -> featuremap3 - > & feature map4. Further, the hidden layers, such as Maxpooling and Convolutional layers, combine to provide more efficient results than existing models.

3.3.11. Pixel Variation

The current research mainly focused on using segmented images with the hippocampus shape; therefore, the provided segmented image was converted to a model for feature-based extraction that is in accordance with the edges and shapes. These models typically help to identify the accurate classes.

However, if the original image has been processed, it is not possible to find the appropriate classes due to the utilization of all features. Table 2,3,4 represents the segmented image pixel count analysis in the hippocampus area. Therefore, the hippocampus place was identified with the red color mark so that the pixel could be counted easily with the red color mark. The ranges are mentioned below for AD and MCI classes:

- CN Cognitive Normal, class images pixel count, ranges greater than 220 in Table 2.
- MCI - Mild Cognitive class image pixel count ranges between 120 to 220 in Table 3.
- AD -Alzheimer's Disease, class image pixel count ranges between 20 to 120 in Table 4.

Further, asymmetry analysis and hippocampus shape occurred by cascaded CNN developed for AD z diagnosis. Here, two models are utilized in the extraction of hippocampus shape features to identify the hippocampus area utilizing the model; the results are provided in the CNN model.

Further, the model 'sequential' has been represented in table 5 with layer type, output shape, and parameters. The proposed method - Opti Multi-Hidden Deep Rooted Neural Networks with the improved method utilizing the Dwarf Mongoose Optimization Algorithm (DMOA) to execute the effective parameters for the Neural Network. The parameters in the research are optimized utilizing DMOA as follows:

- Neurons Count - Here, the number of neurons present in every hidden layer that is identified for N1 - N8 was optimized. DMOA includes different values for the represented parameters to identify the yielded combination with the best performance.
- Dropout - The rate of dropout was optimized and known as a regularization technique utilized to prevent issues such as overfitting in NN. Normally, DMOA searched, especially for the optimal rate of dropout that enhanced the model generalization.
- Learning Rate - Here, the learning rate was optimized, which defines the step size presented in the optimization process, and DMOA identifies the value using the learning rate that enabled the technique to converge more rapidly and reach effective performance.
- Epochs - The number of epochs was optimized by iteratively training the considered data numerous times during the training phase. And also defines the epoch optimal number that balances amidst overfitting and underfitting issues that result in effective performance.
- Activation Function - The activation function utilized for every layer was optimized, which initialized nonlinearity in NN that affected the capability of the technique in learning the difficult patterns. Certainly, DMOA considers various activation functions, including softmax, sigmoid, and Relu, to define the most appropriate ones for every layer.

The Optimized DMOA algorithm was utilized to systematically estimate and search different combinations of the selected parameters to identify the optimal configuration that enhances the Opti Multi Hidden Deep Rooted Neural Networks performance.

Table 2. CN - Cognitive Normal class images pixel count ranges from Greater than 220

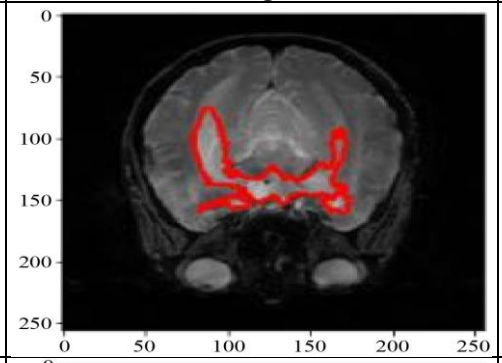
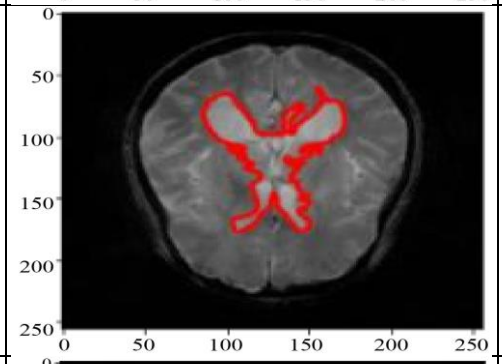
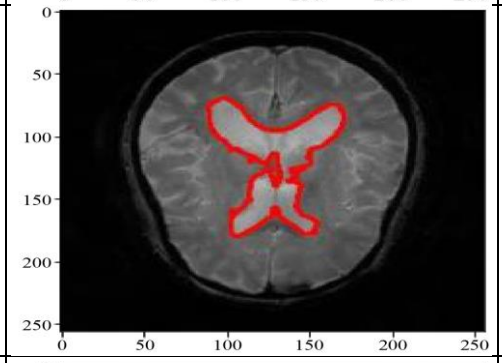
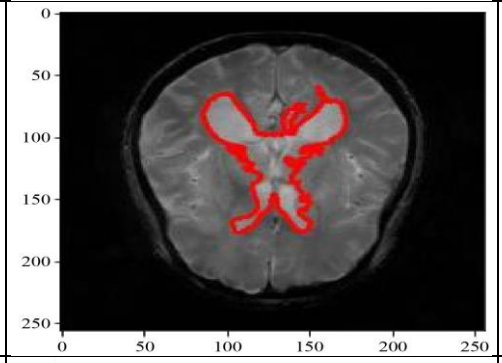
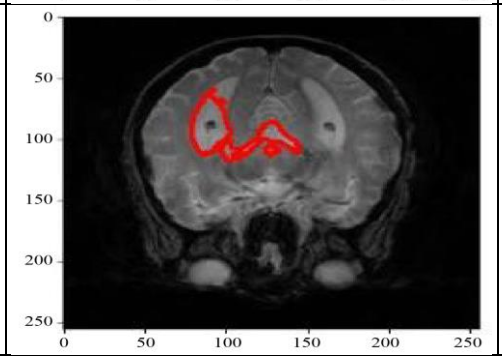
No	Image	Pixel
1		237
2		378
3		276
4		354
5		267

Table 3. MCI - Mild Cognitive class images pixel count ranges from 120-220

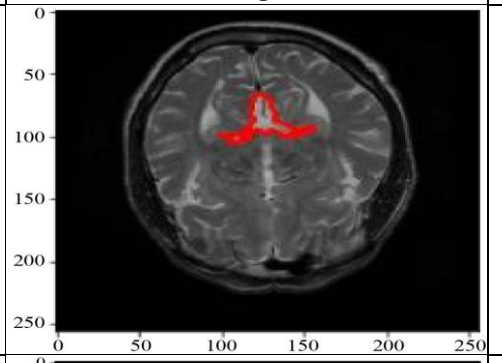
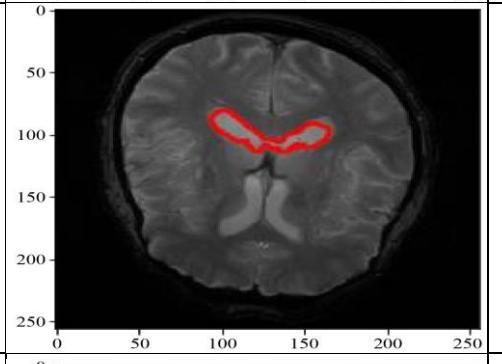
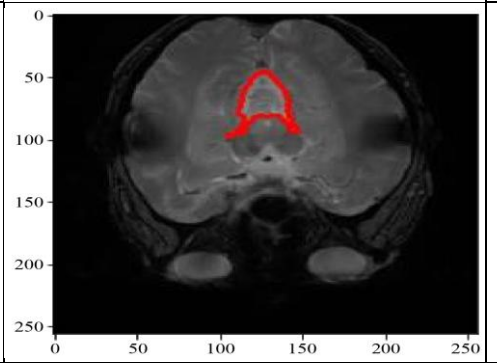
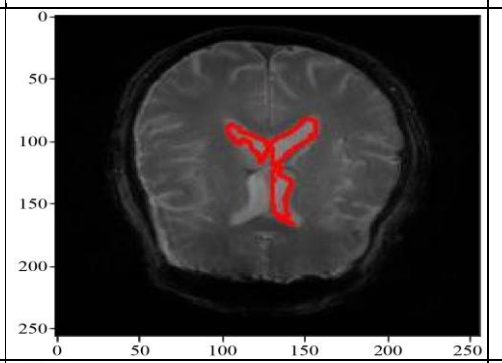
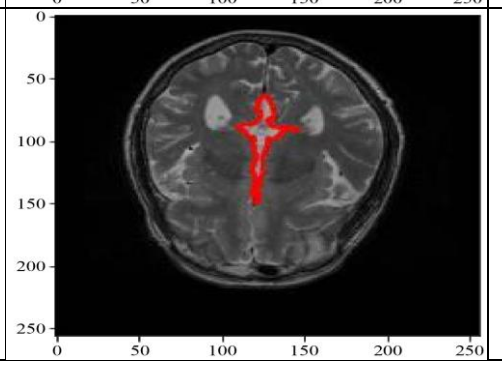
No	Image	Pixel
1		200
2		189
3		123
4		153
5		219

Table 4. AD – Alzheimer Disease class images pixel count ranges from 20-120

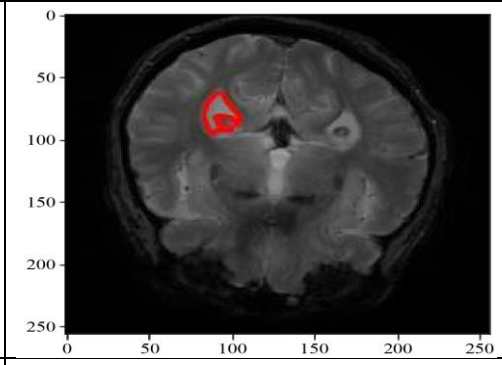
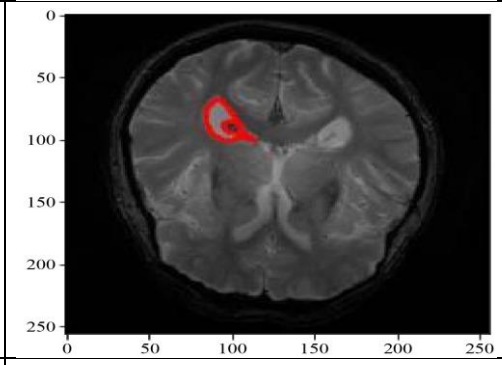
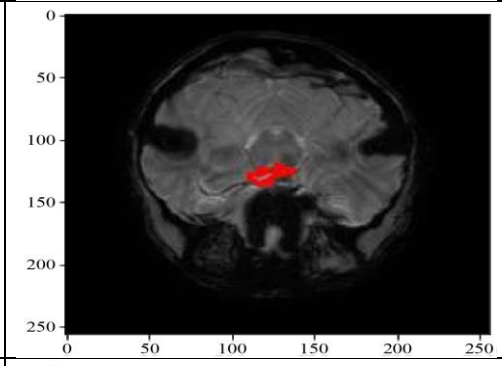
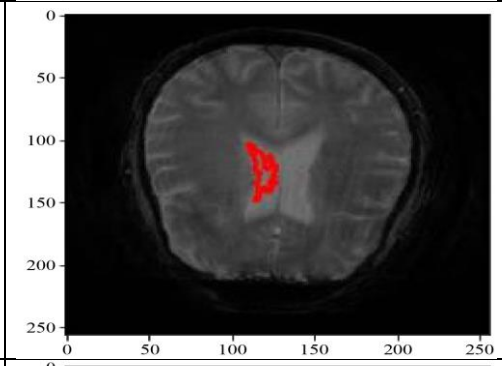
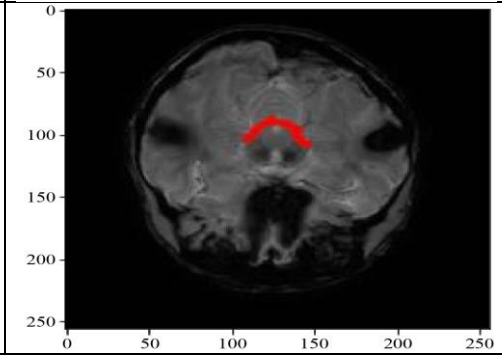
No	Image	Pixel
1		66
2		63
3		24
4		117
5		81

Table 5. Model: "sequential" with Layer type, output shape, and parameters.

```
Input (Image)
    |
Conv2D (16 filters)
    | MaxPooling2D
    |
Conv2D (32 filters)
    | MaxPooling2D
    |
Conv2D (64 filters)
    | MaxPooling2D
    |
Conv2D (128 filters)
    | MaxPooling2D
    | Flatten
    |
Dense (1024 units)
    | Dropout
    |
Dense (512 units)
    | Dropout
    |
Dense (128 units)
    | Dropout
    |
Dense (64 units)
    | Dropout
    |
Dense (3 units) [Output]
```

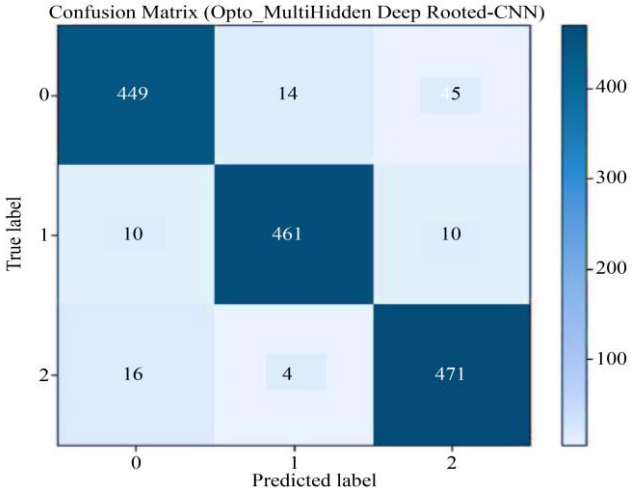


Fig. 4(a) Confusion Matrix (Proposed Method - Opti Multi-Hidden Deep Rooted CNN)

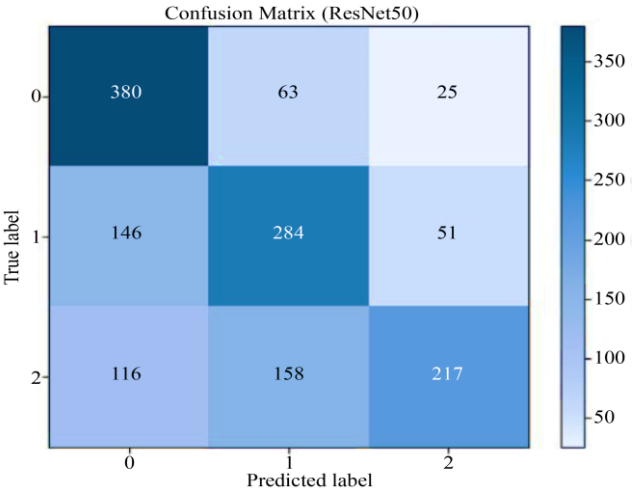


Fig. 4(b) ResNet50

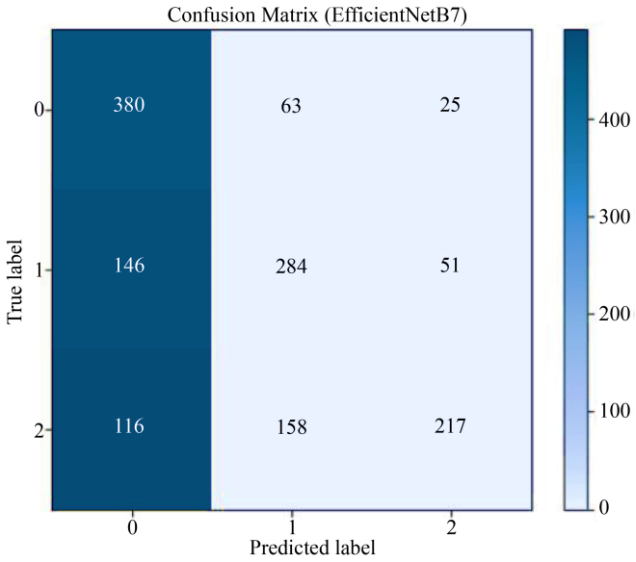


Fig. 4(c) EfficientNetB7

4. Proposed Results and Analysis

In the data and analysis section, the newly proposed innovative approach - Opti MultiHidden Deep Rooted CNN results on the identification of the AD with the symptoms and in accordance with the brain MRI for novel segmentation utilizing improved deep learning methods has been represented. Therefore, the proposed approach has been evaluated in comparison to the current methodologies. such as ResNet50 and EfficientNetB7. The confusion matrix of the proposed model - Opti Multi-Hidden deep Rooted CNN, with existing research ResNet50 and EfficientNetB7, has been depicted in Figures 4a, 4b, and 4c. Moreover, the proposed model has been evaluated with the validation loss, and accuracy with epochs has been illustrated in the graphical representation in Figures 5a and 5b. The proposed model has been evaluated with the validation loss, and the accuracy of ResNet50 and EfficientNetB7 models with epochs have been represented in the graphical representation in Figures 5c, 5d, 5e, and 5f. Eventually, the comparison table on the proposed method is depicted in Figure 6 based on the performance metrics such as MAP, F1-score, recall, precision, and accuracy.

Accuracy (acc) = TPP + TNN / Total number of samples

TPP - True Positive, TNN - True Negative

Precision (pre) = TPP / (TPP + FPP)

TPP - True Positive, FPP = False Positive Recall (rc) = TPP / (TPP + FNN)

FNN - False Negative

F1 - Score (f1) = 2 x (Precision(pre) x Recall(rc)) / (Precision(pre) + Recall(rc))

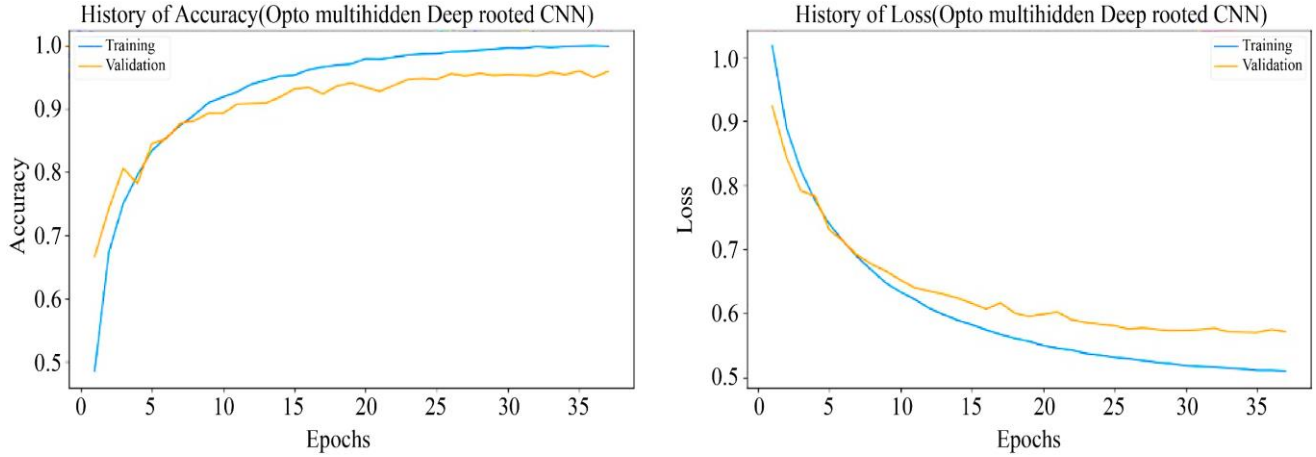


Fig. 5 (a) Training & Validation Accuracy of Opti MultiHidden Deep Rooted CNN (b) Training & Validation Loss of Opti MultiHidden Deep Rooted CNN

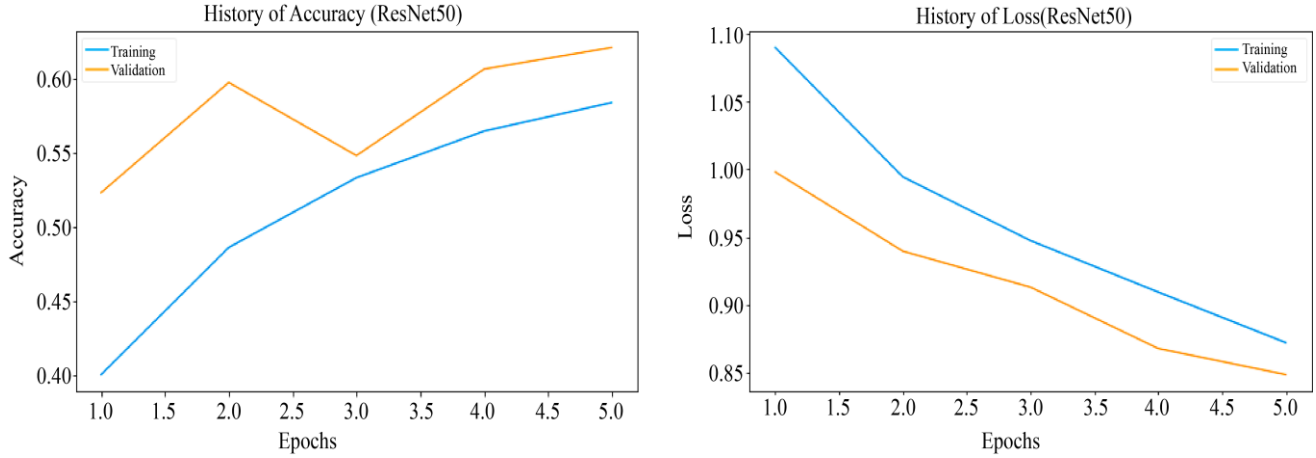


Fig. 5 (c) Training & Validation Accuracy of ResNet50 (d) Training & Validation Loss of ResNet50

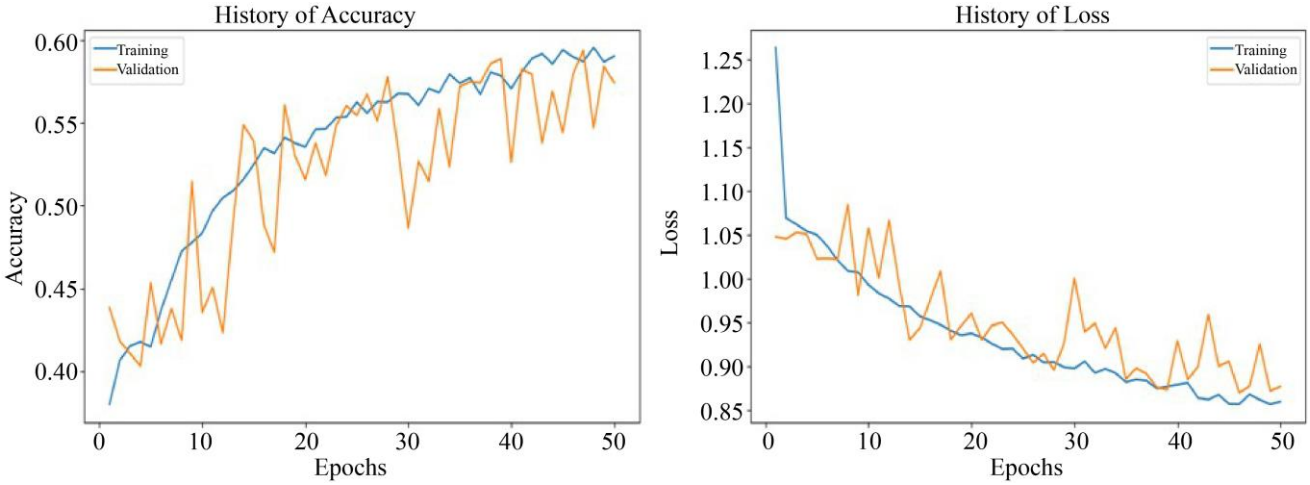


Fig. 5 (e) Training & Validation Accuracy of EfficientNetB7 (f) Training & Validation Loss of EfficientNetB7

Figure 5a. and Figure 5b. illustrating the training process of Opti multi-hidden Deep rooted CNN. The x-axis represents epochs, which corresponds to a complete iteration of the training data. The y-axis of the left graph reflects accuracy, whereas the y-axis of the right graph shows loss.

Figure 5a. illustrates a positive correlation between the model's accuracy and the number of epochs. This indicates that the model is progressively improving its ability to categorize images with more accuracy as time goes on. Figure 5b. depicts a declining trend in loss as the number of epochs increases. Loss quantifies the extent to which a model's predictions deviate from the actual values. A decline in loss signifies an improvement in the model's predictive accuracy. In Figures 5c and 5d, the x-axis represents epochs, which corresponds to a full iteration of the training data. In the left graph, the y-axis reflects accuracy, whereas in the right graph, the y-axis shows loss.

Figure 5c illustrates a positive correlation between the accuracy and the number of epochs. This indicates that the model is progressively improving its ability to categorize photos with more accuracy as time goes on. Figure 5d illustrates a progressive decline in loss as the number of epochs grows. A decrease in loss signifies an improvement in the accuracy of the model's predictions. Similarly, Figures 5e and 5f represent the accuracy and loss graph for the EfficeinetNetB7 model, respectively. Similarly, Figures 5e and 5f represent the accuracy and loss graph for the EfficeinetNetB7 model, respectively. Figure 6 is a bar graph comparing the performance of three classification algorithms based on accuracy, f1- score, recall, precision, and MAP. Graphs x-axis displays the algorithms EfficientNet, ResNet50, and Opti Multi-Hidden Deep Rooted CNN. The y-axis represents the achieved score, where higher values indicate superior performance. The proposed method has achieved the greatest MAP score of 0.93, surpassing existing methods.

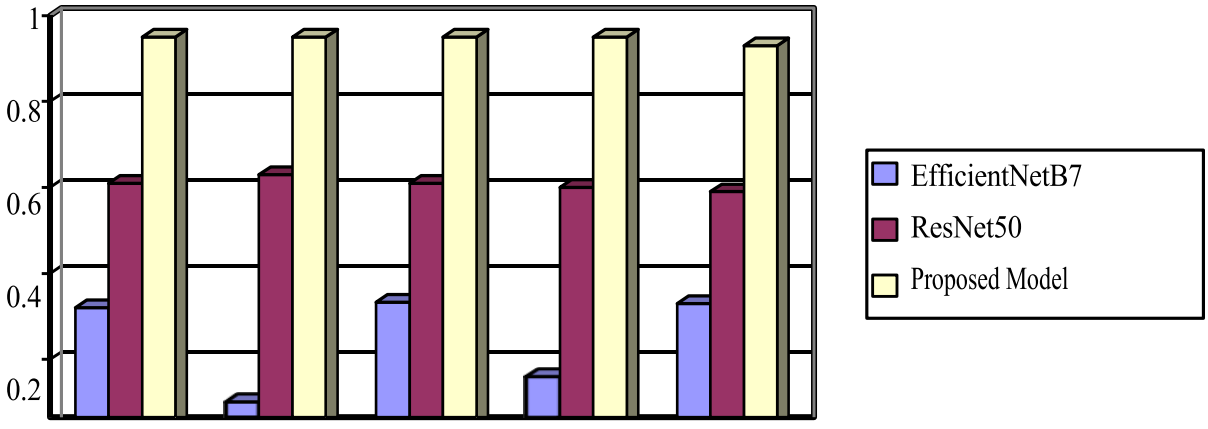


Fig. 6 Comparison of proposed method - Opti MultiHidden Deep Rooted CNN with existing classification algorithms - ResNET50 and EfficientNetB7

Table 6. Performance Evaluation (PE) of the proposed method with existing methods

Model	Accuracy	Precision	Recall_score	F1_score	MAP
EfficientNetB7	0.32	0.10	0.33333	0.16	0.33
ResNET50	0.61	0.63	0.61	0.60	0.59
Proposed Model (Opti Multi-Hidden Deep Rooted Convolutional Neural Network)	0.95	0.95	0.95	0.95	0.93

5. Conclusion

The current mainly focused on the proposed novel method. The image classification problems were solved using Opti MultiHidden Deep rooted CNN for early diagnosis of AD. The proposed method Opti- Multi Hidden Deep rooted Convolutional Neural Network has been compared in terms of certain significant factors that include MAP - Mean-Average-Precision of 95%, F1-score of 95%, recall of 95%, precision of 95%, and accuracy of 93%. Hence, the proposed method has been compared with the existing techniques, such as ResNet50 and EfficientNetB7, and obtained higher results than existing methods. Eventually, the proposed system obtained more efficient results compared to the other existing methods. In the future, large real-time datasets will be used with the integration of the proposed system to enhance accuracy and sensitivity.

Data Availability

The data has been collected from ADNI datasets https://ida.loni.usc.edu/login.jsp?project=ADNI

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