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Research Article

Enhanced Computational Neural Structures for Accurate Identification of Depression and Alzheimer's via fMRI

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ABSTRACT

This study presents a inventive approach for classing of depression and Alzheimer's disease patients from normative group using functional Magnetic Resonance Imaging (fMRI) data and deep learning techniques. Leveraging data from the All India Institute of Medical Sciences (AIIMS) and the Alzheimer's disease Neuroimaging Initiative (ADNI), we developed a customized Convolutional Neural Network (CNN) model to accurately categorising between participants with neurological disorders and normal group. Our approach involves preprocessing fMRI data then all fMRI images were converted into 2D PNG format to facilitate analysis. The custom CNN achieved the highest accuracy of 98.06% demonstrating optimal results over two state-of-theart pre-trained networks, including MobileNetV3 and Inception-ResNetV2 assess its efficacy and generalizability. This comparison underscores the advantages of task-specific network architectures in accurately classifying neurological conditions. The findings contribute to the development of reliable, AI-powered diagnostic tools, offering improved accuracy and clinical relevance for timely intervention of depression and Alzheimer's disease.

Keywords: Convolutional Neural Networks (CNN); Deep Learning; fMRI Data; binary Classification; Depression Detection; Alzheimer's Disease

I. INTRODUCTION

In the past several years, the intersection of neuroscience and artificial intelligence (AI) [17] has paved the way for groundbreaking advancements in the timely identification and categorization of neurological conditions [9]. Among these disorders, depression [9] and Alzheimer's disease [30] stand out as significant public health challenges due to their prevalence, impact on quality of life, and societal burden. Depression, defined by ongoing sadness and a decreased enthusiasm for daily tasks, impacts more than 264 million individuals globally, according to the World Health Organization (WHO) [55]. Alzheimer's disease, a degenerative neurological disorder, is the leading cause of dementia in older adults, with approximately 50 million people worldwide affected by dementia [37]. Prompt and precise recognition of these conditions is essential for Strategic care and handling, but it remains a difficult and intricate task for healthcare professionals. Functional Magnetic Resonance Imaging (fMRI) [48] has become a highly effective method for exploring brain activity and connectivity, providing important exploration of the brain mechanisms driving psychiatric and neurological conditions. By tracking changes in blood flow and oxygen levels, fMRI allows researchers to examine abnormal brain patterns linked to disorders such as depression and Alzheimer's disease. This study, leverages data from two well-known neuroimaging repositories: the All India Institute of Medical Sciences (AIIMS) and the Alzheimer's Disease Neuroimaging Initiative (ADNI) https://ida.loni.usc.edu/home/projectPage.jsp?project=ADNI . Using neural network methodologies, with a focus on Convolutional Neural Networks (CNNs), our goal is to create a reliable classification model that can differentiate between individuals with depression or Alzheimer's group and baseline subjects. The core purpose of this study is to fabricate a custom deep learning model specifically for classifying patients with depression and Alzheimer's using fMRI data. The performance of this model will be systematically compared with two advanced pretrained models, Inception-ResNet-v2 [46] and MobileNet v3 [15], to assess its accuracy, effectiveness, and robustness in comparison to these established models. This evaluation will help determine its potential application in clinical diagnostics. The broader aim of this investigation is twofold: to elevate the growing research in neuroimaging-based diagnostic techniques and to provide a potentially transformative tool for timely intervention and recognition in depression and Alzheimer's disease. By harnessing the power of AI and neuroimaging, we aspire to advance clinical practice towards more precise, personalized, and proactive healthcare strategies for individuals at risk of these debilitating conditions.

Contribution of the Study

This research offers several key contributions to the domain of neuroimaging-based diagnostic methodologies and the broader landscape of psychiatric and neurological disorder research:

1) Advanced Classification Model: By utilizing an advanced approach for distinguishing among depression or Alzheimer's groups and normative controls using fMRI data, leveraging neural network methodologies, with a focus on Convolutional Neural Networks (CNNs) The creation of a strong CNN-based model marks an innovative use of state-of-the-art AI technology in neuroimaging analysis..

2) Utilization of Diverse Datasets: Drawing upon data from two prestigious neuroimaging repositories, namely the All India Institute of Medical Sciences (AIIMS) and the Alzheimer's Disease Neuroimaging Initiative (ADNI), this study benefits from the richness and diversity of information captured across different populations and settings. By incorporating data from multiple sources, our research enhances the generalizability and reliability of the classification model.

3) Comparison with Pre-trained Models: In addition to proposing a custom CNN-based approach, this research conducts a panoramic comparative exploration by evaluating the accurate degree of our model in relation to two leading two stateof-the-art pre-trained models. This comparison framework offers important perspectives on the relative effectiveness and appropriateness of various artificial neural networks for the task of classifying neurological disorder patients, thereby informing future research directions and algorithmic refinements.

4) Clinical Implications: By offering a potentially transformative tool for the timely identification and intervention in depression and Alzheimer's disease, this study holds significant clinical implications. The accurate classification of individuals at risk of these debilitating conditions can facilitate timely access to appropriate interventions, personalized treatment plans, and targeted support services, promoting improved patient treatment outcomes and improved well-being.

5) Advancement of Precision Medicine: Through the unification of AI-driven neuroimaging analysis into clinical practice, this research contributes to the paradigm shift toward precision medicine in psychiatry and neurology. By allowing clinicians to leverage objective biomarkers and computational algorithms for diagnostic decision-making, our approach aligns with the broader goal of providing personalized and evidence-based healthcare solutions to individuals with complex neurological disorders.

In summary, this study represents a multidimensional endeavor that combines cutting-edge technology, diverse datasets, comparative analysis, clinical relevance, and the advancement of precision medicine principles to address pressing challenges in the timely identification and categorization of depression and Alzheimer's disease. By pushing the boundaries of interdisciplinary research and innovation, our findings have the potential to catalyze transformative changes in how we understand, diagnose, and treat these conditions, ultimately benefiting individuals, families, and communities worldwide.

The rest of the paper is organized as follows. A detailed literature of previously performed work is shown in Section 2. Section 3 covers the method used in this research and a framework that can classify patients with depression or alzheimer's and normative control groups. Section 4 presents the results and also discusses the results presented. The paper is concluded in Section 5.

II. LITERATURE SURVEY

Payan et al. [32] developed an algorithm for classifying Alzheimer's groups by combining 3D convolutional deep learning models (CNNs) with an autoencoder and 2D CNNs. Their 3D CNN model reached an accuracy of 89.47%, while the 2D CNN model achieved around 85.53%. Another notable study was conducted by Saman Sarraf et al. [39],[40], where they created a comprehensive pipeline for classifying Alzheimer's group and normative subjects using both fMRI and MRI data. Their approach utilized two different methods for binary classification, leveraging CNN architectures like LeNet-5 [38] and

GoogLeNet [34], with the LeNet model achieving an average accuracy of 97.5% on fMRI data. Kazemi [21] applied the AlexNet CNN to fMRI datasets to categorize five levels of Alzheimer's disease, obtaining an average accuracy of 97.63%.This method demonstrated significant improvements over previous studies, with class-specific accuracies ranging from 94.55% to 98.34%. Abrol et all [1] supports the exploration of multimodal data fusion frameworks to improve the prediction of functional alterations in neuroimaging data. By including the capabilities of both sMRI and fMRI, his method offer promising directions for early diagnosis and treatment planning in neurodegenerative diseases like Alzheimer's. Duc [11] research demonstrated that using a 3D CNN on rs-fMRI data achieved an 85.27% accuracy in diagnosing Alzheimer's disease, and predicted MMSE scores with high precision, employing feature optimization techniques such as LASSO and SVM-RFE for improved performance . Gupta [19] introduced the ambivert degree, a measure that considers both node degree and connection weights to accurately identify brain hubs using rs-fMRI data for classification accuracy of Alzheimer's and Autism Spectrum Disorder patients compared to traditional functional connectivity features. Ju [18] advancements in computerized healthcare demonstrate that integrating deep learning with brain network features and clinical data significantly enhances early Alzheimer's disease diagnosis, achieving a

31.21% improvement in prediction accuracy and a 51.23% narrowing of dispersion compared to traditional methods. Li [25] introduced a 4D deep model (C3d LSTM) for diagnosing Alzheimer's disease, leveraging 4D fMRI data to gather spatial and temporal insights. This model significantly outperformed approaches using functional connectivity or 2D/3D fMRI data, underscoring the importance of retaining natural spatiotemporal details in medical imaging. Parmar [31] demonstrated the use of a modified 3D CNN on resting-state fMRI data for Alzheimer's classification, preserving both spatial and temporal information. This method effectively distinguished between normative controls, mild cognitive impairment (MCI), and Alzheimer's group, highlighting its potential for early detection and improved diagnosis. Ramzan [35] applied resting-state fMRI and the ResNet-18 architecture for differentiation of Alzheimer's disease into multiple stages, achieving state-of-the-art accuracy of 97.92% with an off-the-shelf model and 97.88% with a fine-tuned version. This research emphasizes the potential of advanced deep models for timely diagnosis and enhanced clinical selection process in neurodegenerative conditions. Tajammal [45] proposed a two-step deep neural network based approach for Alzheimer's diagnosis, attaining 98.8% accuracy in classifying six stages of the disease using MRI scans. This method involved binary classification of MCI and AD, followed by multi-class categorization, which was further improved using max-voting ensembling techniques. Shamrat [43] introduced a fine-tuned CNN model, AlzheimerNet, which achieved a test accuracy of 98.67%, outperforming existing models in identifying six levels of Alzheimer's disease from MRI scans and surpassing traditional methods.

Limitations of previous studies:

Although the cited studies provide important insights into the use of AI and neuroimaging for classifying depression and Alzheimer's disease, several limitations can be identified, presenting opportunities for improvement and innovation in the present research:

- Limited Generalizability: Many existing studies focus on single-site data or specific populations, which may limit the generalizability of their findings. By leveraging data from multiple sources, including AIIMS and ADNI, the cited research has the potential to improve the diversity and representativeness of the study cohort, resulting in more robust and widely applicable classification models.

- Feature Representation: Some studies rely on handcrafted or predefined features extracted from neuroimaging data, which may overlook subtle but important patterns relevant to disease classification. By employing deep learning techniques, such as CNNs, the present research is capable of learning hierarchical structures without manual intervention directly from fMRI data, potentially capturing more informative and discriminative features for improved classification performance.

- Interpretability: Deep learning models are frequently criticized for their limited interpretability, making it difficult to comprehend the reasoning behind their classification decisions. Incorporating techniques for model interpretability, such as feature visualization or attention mechanisms, can enhance the transparency and trustworthiness of the classification framework, enabling clinicians to better interpret and validate the results.

- Data Imbalance: Class imbalances, where one class (e.g., Alzheimer's patients) may be significantly underrepresented compared to others (e.g., healthy controls), can pose challenges for training robust classification models. Utilizing methods like data augmentation, oversampling, or incorporating class weights during training can help address data imbalance and improves the system's ability to accurately classify minority groups.

By overcoming these limitations and expanding on current research, this study can push forward advancements in AI-driven neuroimaging analysis for classifying depression and Alzheimer's disease, leading to more precise, interpretable, and clinically applicable diagnostic tools.

III. MATERIAL AND METHOD

A. Dataset Description

The meticulously curated datasets, annotated by specialists and sourced from various channels, include fMRI scans from ADNI and AIIMS dataset shown in Figure 1 and Figure 2 respectively. Both datasets have undergone rigorous preprocessing using SPM12, ensuring high-quality inputs for the deep learning models. The preprocessing steps—such as slice timing correction, realignment, normalization, and smoothing—are essential for improving the signal-to-noise ratio and ensuring consistent data standardization across subjects.

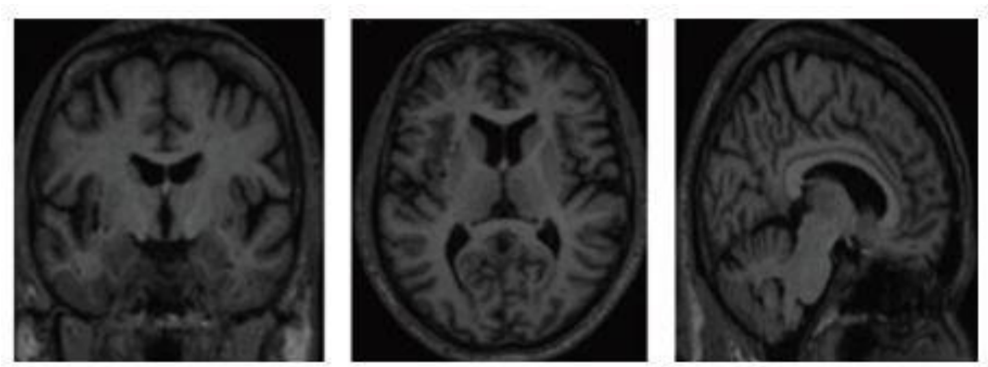


Figure 1: fMRI scans ADNI Dataset (Coronal, Axial, and Sagittal views from left to right)

fMRI data inherently contains rich spatial and temporal information about brain activity, making it ideal for deep learning approaches that thrive on complex, high-dimensional data. This characteristic allows the custom model and the pretrained models to potentially capture nuanced patterns associated with each condition. The datasets include a substantial number of subjects with varying degrees of depression and Alzheimer's, providing a comprehensive representation of these conditions. This assortment is crucial for training models that can effectively extend across various patient groups.

For the Alzheimer's dataset , 15 patients and 10 healthy participants with an average age of 64.5 were selected from the ADNI database. Scanning for ADNI data employed 3T MR scanners, covering both structural and functional scans. The functional scans were performed with a voxel size of 3 x 3 x 3 mm, a repetition time of 2 seconds, an echo time of 30 ms, a flip angle of 70 degrees, and a 20 cm field of view with a 64 x 64 matrix.

The Depression dataset involved recruiting 30 patients and 10 healthy controls from the AIIMS outpatient center in India . Using a 1.5 T MR scanner, fMRI data acquisition included functional scans with parameters such as a voxel dimension of 2 x 2 x 2 mm, repetition time of 2 seconds, an echo time of 26.3 ms, and a field of view measuring 25.6 cm with a 256 x 256 matrix. A total of 128 slices, each 5 mm thick, were obtained.

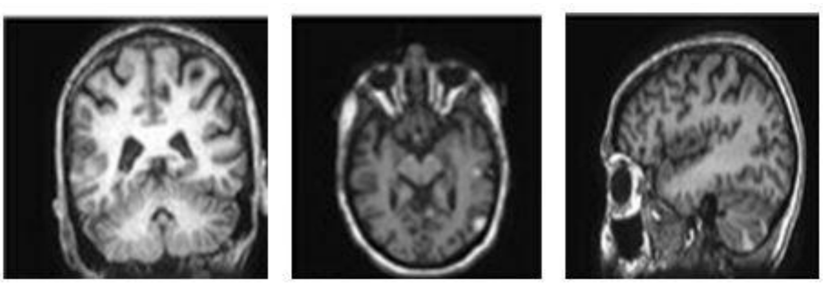


Figure 2: fMRI scans AIIMS Dataset (Coronal, Axial and Sagittal views from left to right)

B. Methodology

This section outlines the framework used in our research, covering the preprocessing of raw fMRI images, model training, and evaluation. The process begins with data preprocessing to remove anomalies, reduce noise, and standardize the dataset. Following this, feature extraction is accomplished using a custom Convolutional Neural Network (CNN) for image recognition. In this study, we conducted binary classifications for Alzheimer's disease (AD) and Depression. The custom CNN was used to classify scans into two categories: Alzheimer's vs. Controls and Depression vs. Controls. For multiclass classification, we utilized various CNN models, which were combined with the custom CNN to form an ensemble of models. Figure 3 illustrates the detailed methodology.

1) Data Preprocessing: The preprocessing of raw fMRI images is an essential step to ensure that the data are clean, compatible, and ready for analysis by deep learning models. This process involves several sequential stages, which are detailed below:

Two diverse data sets were used for this study, each containing fMRI scans from subjects diagnosed with depression, Alzheimer's, and healthy controls. (Details were explicitly presented in the previous section). The data set explored here consists of fMRI scans in NIfTI format.

Preprocessing of the raw fMRI data was conducted using SPM12, a software package widely used for the analysis of cerebral imaging data. The steps included are as follows:

1) Slice Timing Correction: This step addresses the time differences in slice acquisition within each fMRI volume. This is crucial because fMRI data is acquired in a sequential manner, meaning different slices are captured at slightly different times. It aligns the time courses of voxels in different slices by interpolating the data, effectively adjusting the data as if all slices were acquired simultaneously.

2) Realignment: To correct for head movements that occur between scans. Even slight movements can introduce artifacts that affect the analysis. It utilizes a rigid body transformation to align all images in a time series to the first image (or a mean image). This step involves estimating the movement parameters and applying them to realign all volumes.

3) Coregistration: It is a vital preprocessing step in fMRI data analysis, aimed at aligning images from different modalities

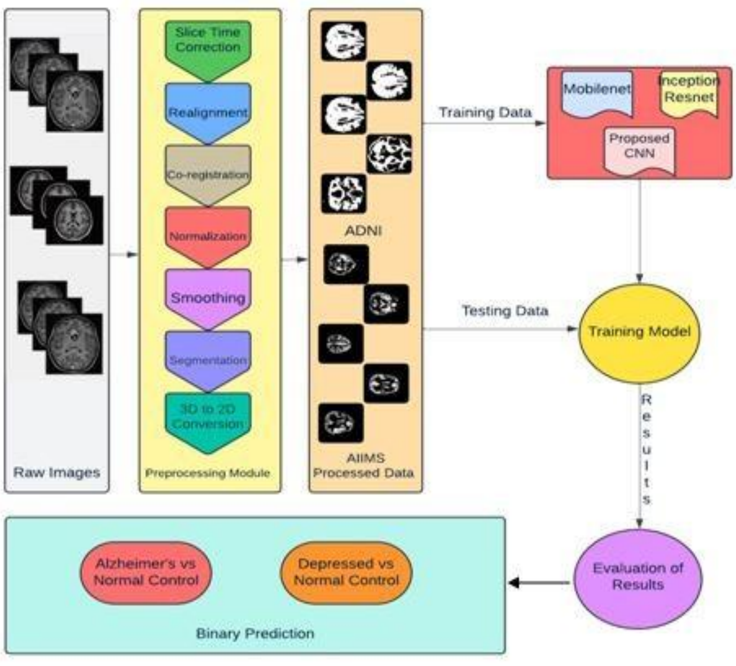


Figure 3: Methodology

or different time points to a common space. This step is essential for ensuring that anatomical and functional data correspond accurately across different scans.

4) Normalization: To map the fMRI data from individual subjects into a standardized anatomical space, typically based on a template such as the Montreal Neurological Institute (MNI) space. It involves spatially transforming each participants brain image to match a conventional template. This allows for meaningful comparison and averaging across subjects.

5) Smoothing: Aims to enhance the signal-to-noise ratio and to accommodate individual structural variations by averaging the data over a specified spatial scale. This step applies a Gaussian kernel to the fMRI images, blurring the data slightly to enhance the signal. The size of the kernel (e.g., 6-8 mm FWHM (full-width at half-maximum)) is chosen based on the scale of the expected effects.

6) Segmentation: It is a preprocessing step in fMRI analysis where the brain image is divided into different tissue types. This step is crucial for isolating regions of interest, enhancing the precision of functional analysis, and facilitating more detailed anatomical studies. The primary tissue types segmented usually include grey matter (GM), white matter (WM), soft tissue, and cerebrospinal fluid (CSF).

7) Conversion into 2D images: To transform the 4D fMRI data (3D spatial + time) into a format suitable for input into 2D convolutional neural networks. The segmentation results in the 4 tissues and total of 700 and 129 for ADNI and AIIMS data respectively segmented images of each patient as well as control, which result in 64 × 64 × 84 × 128 scans , with each scan including 64 × 64 3D-84 volumes per scan (a total of 128 scans)for ADNI data and 64 × 64 × 29 × 140 scans with each scan including 64 × 64 3D-29 volumes per scan (a total of 140 scans) for AIIMS data.

After the conversion process, selection criteria of images are done using entropy. In image processing, entropy quantifies the level of information or randomness in an image. A higher entropy value signifies greater complexity and variation in pixel intensity, indicating that the image contains more detailed and useful information. Conversely, lower entropy implies less variability and potentially redundant or less informative data. By calculating the entropy of each image, we can assess its information content and make informed decisions about which images to retain for analysis as explained in algorithm 1.

Entropy H of an image is calculated using the probability distribution of pixel intensities. Mathematically, it is defined as:

$$H_i = -\sum_{p \in P_i} p \cdot \log_2(p) \qquad (1)$$

where:

- p(i) represents the probability of the i-th intensity level in the image.
- n depicts the total number of possible intensity levels (for example, 256 in an 8-bit grayscale image).

Algorithm 1 Entropy-Based fMRI Image Selection

Require: 2D fMRI images I with probability distribution of pixel intensities H_{image}

Ensure: Selected fMRI images

0: Compute the entropy value of the image using the entropy formula.

0: Determine an appropriate entropy threshold $H_{\text{threshold}}$.

0: for each image I do

0: if Himage ≥ Hthreshold then 0: Retain the image.

0: else if Himage < Hthreshold then 0: Discard the image.

0: end if

0: end for

=0

By applying this entropy-based selection method, the dataset is refined to include only those images that are likely to provide valuable information for training the deep neural network model. Table 1 presents the number of images collected. These preprocessing steps aim to standardize the fMRI data, reduce noise, and format it appropriately for training deep learning models, potentially improving model performance and leading to more accurate classification results. The result is a set of high-quality 2D images that accurately reflect the underlying brain activity, providing a robust foundation for model training and subsequent analysis.

Dataset	Patients	Controls
AIIMS (20-P)	14811	2949
ADNI (30-P)	14946	3338

Table I: Number of Images obtained

C. Classification

The preprocessed fMRI data is converted into 2D images of size 224 x 224, which serve as the input for the deep learning models. This paper include three Convolution neural networks to train fMRI dataset and tested results framed the best CNN for above mentioned datasets.

- Mobile netV2: MobileNet V2 is a deep learning model designed for efficient performance [23]. It builds upon the original MobileNet architecture, introducing several enhancements to improve both accuracy and speed while keeping the model lightweight. MobileNet V2 [42] is an advanced, efficient neural network architecture designed to perform well on mobile and embedded devices. It aquires this through the use of depthwise separable convolutions, inverted residuals with linear bottlenecks, and an overall design focused on reducing computational cost while promising quite good accuracy. This makes MobileNetV2 an impactful choice for real-time image processing on devices with constrained computational power

[5].

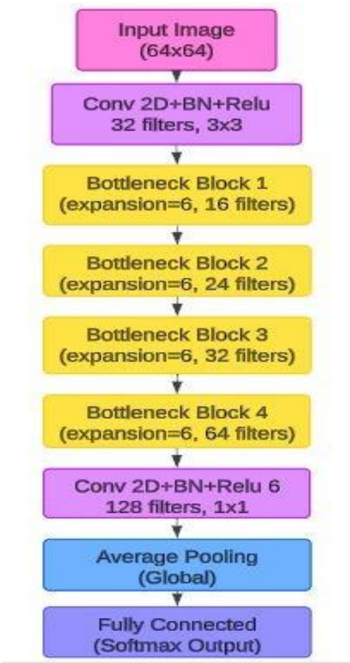


Figure 4: Architecture of Mobilenet v2

• Inception Resnet : Inception-ResNet [10] combines the strengths of two influential neural network architectures: the Inception architecture, known for its multi-scale feature extraction [27], and Residual Networks (ResNet) [52] enable the efficient training of quite deep neural networks. It was designed to escalate both the training efficiency and accuracy of deep learning models by leveraging the complementary strengths of these architectures. Inception-ResNet represents a powerful and an efficient deep learning models that leverages the combined reinforce of Inception modules and residual connections. Its design allows for effective multi-scale feature extraction, stable and efficient training of deep networks, and adaptability to various image processing tasks. This makes Inception-ResNet [3] a valuable tool in both research and practical applications, including medical imaging, where it can can greatly improve the accuracy and efficiency of diagnostic models.

Inception-ResNet has proven itself to be a top performer across multiple benchmark image classification datasets, including the widely recognized ImageNet [29]. Its strength lies in its robust feature extraction capabilities, making it a go-to architecture for transfer learning in diverse vision tasks [44]. By combining the best of Inception modules and residual connections, it provides an exceptionally powerful backbone for deep learning models, allowing them to tackle complex image-based problems with remarkable precision and efficiency.

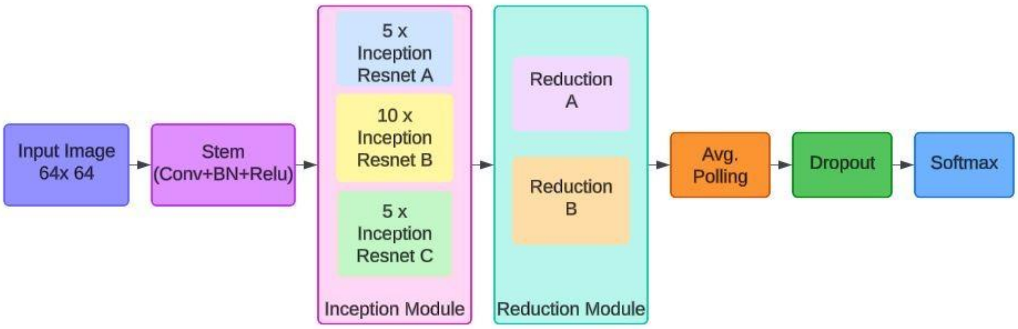


Figure 5: Inception-Resnet v1 architecture

In this research, we employ a systematic technique to categorize images using 2 pretrained and one custom CNN into two categories: patient and control. The detailed steps of algorithm using pretrained network are as provided in Algorithm 2.

Algorithm 2 Training a Classification Model

Require: Dataset D containing images x_i and labels y_i.

Ensure: Trained Classification Model $N_{trained}$, Model accuracy A. 0: Initialize Dataset D(x_i,y_i).

0: Split D into training set D_{train} and test set D_{test}.

0: Load the pretrained network N_{pre}.

0: Modify layers of the network:

0: Remove final layers and add custom layers for binary classification to N_{pre}.

0: N_{mod} = Remove Layers(N_{pre}).

0: N_{mod} = Add New Layers(N_{mod},numClasses = 2).

0: Specify learning rate α, batch size m, and number of epochs E.

0: Train Network using:

0: Ntrained = TrainNetwork(Nmod,Dtrain,α,m,E).

0: Evaluate the trained network $N_{trained}$ on D_{test} and calculate accuracy:
0: $\overline{\quad\quad}$ $|D_{test}|$. =0

A = correct predictions

• Custom CNN: Convolutional Neural Networks (CNNs) [26] are a specialized deep learning based neural network architecture fabricated to handle grid-like data, such as images. Due to their feasibility that they absorb spatial hierarchies of features through backpropagation, CNNs are highly effective in image recognition and classification tasks [49]. Figure 6 illustrates the architecture of a basic CNN model.

A prototypical CNN architecture includes [22] an input layer, multiple convolutional layers with ReLU activations, pooling layers, a flattening layer, fully connected (dense) layers, and a final softmax layer for classification. This combination of layers enables the network to efficiently learn and classify complex patterns from image data [7], making CNNs ideal for a wide range of computer vision tasks.

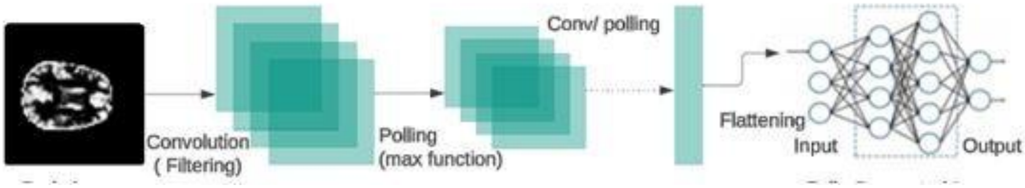


Figure 6: CNN Architecture

CNNs process input images through a series of specialized layers, each serving a distinct function. Algorithm 3 demonstrates the steps for a custom CNN, starting with the input layer, which processes images of size 224×224. The convolutional layers apply filters to extract features from the image, mathematically represented as:

$$(I * K)(i,j) = \sum_m \sum_n I(i-m, j-n)K(m,n) \quad (2)$$

Where I is the input image and K is the filter (kernel). Following the convolution, the ReLU activation function introduces non-linearity, represented as:

$$f(x) = max(0,x) \quad (3)$$

A batch normalization layer is used to stabilize the training process by normalizing outputs, defined as:

$$\hat{x} = \frac{x-\mu}{\sqrt{\sigma^2+\varepsilon}} \quad (4)$$

Where μ and σ^2 represent the mean and variance, respectively. Next, the max-pooling layer reduces the spatial dimensions by adopting the max number in 2×2 window [13], mathematically expressed as:

$$y_{(}i,j) = max(x_{(}m,n)), form, npoolingwindow \quad (5)$$

A dropout layer is then applied during training to prevent overfitting, randomly setting a fraction ppp of input units to

zero:

$$Y\,i = x_i/(1-p) \quad (6)$$

The flatten layer transforms the 2D feature maps into a 1D vector, preparing the data for the fully connected layers (Dense layer) [41], which connects every neuron to all neurons in the previous layer, mathematically represented as

$$y = f(Wx + b) \quad (7)$$

where W is the weight matrix, b is the bias, and f is typically ReLU activation function. Finally, the output layer produces classification probabilities using the softmax function,

$$\sigma(z)_j = \frac{e^{z_j}}{\sum_k e^{z_k}} \quad (8)$$

ensuring the outputs sum to one, suitable for binary classification. Each layer's contribution enables the CNN to learn hierarchical features and make accurate classifications [6]. The CNN model includes the following key layers: Input layer: Receives the input image, normalizing pixel values from [0, 224] to [0, 1]. Convolution layer: Uses 16 filters (3×3) and the ReLU activation function as shown in Equation (2). Max-pooling layer: After three convolutional layers, this layer reduces the dimensions using Equation (3). Batch normalization: Applied after max-pooling to stabilize training and normalize outputs. Additional convolutional layers: Consisting of 32 filters (3×3) with ReLU activation, followed by max-pooling and batch normalization. Fully connected (dense) layer: Contains 128 units, each connected to every neuron from the previous layer, using the ReLU activation function. Another dense layer: With 64 units, this layer is also activated by the ReLU function. Dropout layer: A dropout rate of 0.25 is applied to prevent overfitting by setting 25% of the neuron outputs to zero during training, enhancing generalization. Final fully connected layer: Consisting of 2 units, this layer uses the softmax function for classification.The architecture of the proposed CNN model is visually represented in Figure

7.

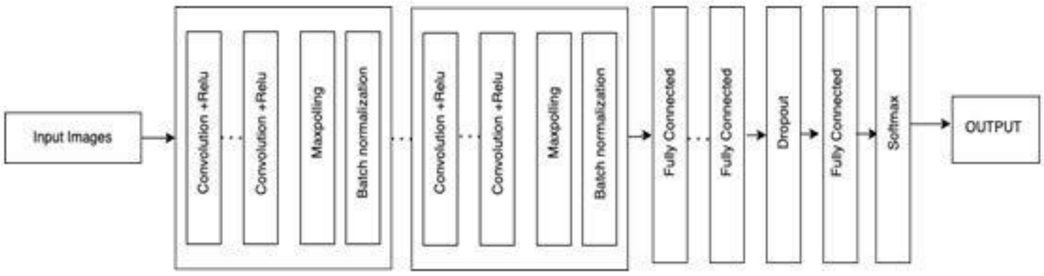


Figure 7: Proposed customized CNN model

IV. RESULTS

This section outlines the analysis and experimental results, underlined the performance and productiveness of the suggested models and two pretrained networks on two distinct datasets for binary classification tasks. The classification tasks involved distinguishing between:

- Depression vs. Controls using AIIMS dataset.
- Alzheimer's Disease vs. Controls using ADNI dataset.

The final results were based on the average values of evaluation metrics such as accuracy, specificity, sensitivity, recall, and F1 score. Additionally, the training and testing times were recorded. Section 4.1 provides comprehensive details about the workspace setup. The models' performance was assessed using the datasets described in Section 4.2, and a comparative analysis of the findings is presented in Section 4.3.

A. Working Characteristics

All programming for the deep neural networks was conducted using MATLAB 2023a. The hyperparameter and default settings for the models, such as the selected optimizer, loss function, and maximum number of epochs, are summarized in the table II

These configurations were selected to enhance the training process and ensure strong performance across various datasets.

CNN Model	Parameter
Mobilenet v2	Optimizer = adam Loss Function = crossentropy Epochs = 10 Mini Batch Size = 100

	Initial Learning Rate = 0.001 Validation Frequency = 100
Inception resnet	Optimizer = adam Loss Function = crossentropy Epochs = 10 Mini Batch Size = 100 Initial Learning Rate = 0.001 Validation Frequency = 100
Custom CNN	Optimizer = rmsprop Loss Function = crossentropy Epochs = 20 Mini Batch Size = 50 Initial Learning Rate = 0.002 Validation Frequency = 30

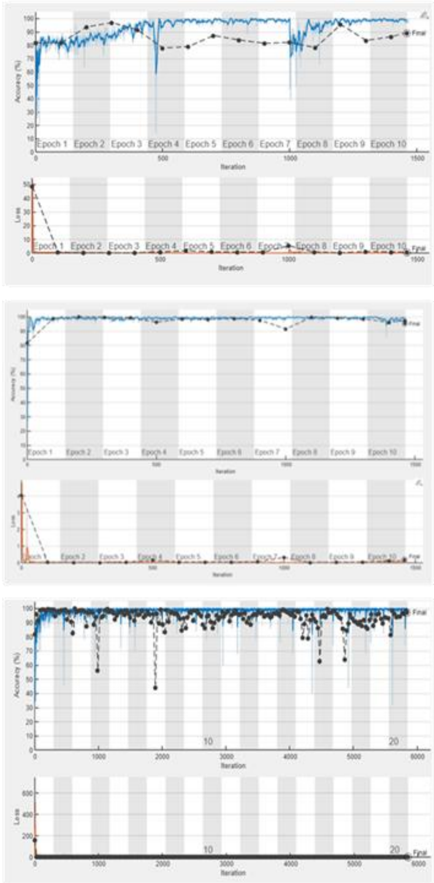
Table II: CNN Model Parameters used

B. Training Progress

The training progress for the binary classification of depression vs. controls using the AIIMS dataset and Alzheimer's Disease vs. controls using the ADNI dataset is a plot of accuracy and loss over iterations of training on training as well as validation data for the custom CNN, MobileNetV2, and InceptionResNetV1 models. The top panel depicts the accuracy trends over iterations, while the bottom panel represents the loss trends.

In Figure 8, (a) shows the training progress of Mobilenet. The training accuracy (blue line) starts at a lower value and improves steadily over iterations, reaching near 100% in the later epochs indicates the model successfully learns the training data features. Also, the training loss (orange line) decreases significantly during the early epochs, stabilizing near zero reflects effective learning and optimization. The figure (b) shows the training progress of inception resnet v2, the training accuracy line shows rapid movement during initial epochs while the validation starts at a low level but improves steadily, reaching final value of 95.38%. This class alignment between training and validation accuracies indicates minimal overfitting and good generalization to unseen data. The figure (c) illustrates the training progress of custom CNN model, the training and validation accuracy trends are represented by the solid blue and dashed black lines, respectively. The final validation accuracy achieved was 97.29%, indicating the model's high performance on unseen data. In the lower graph, the loss function values decreased rapidly during the initial iterations and plateaued in later stages, demonstrating effective convergence of the model.

Figure 9, (a) shows the training progress of the Mobilenet v2 model, with the top graph representing accuracy and the bottom graph depicting loss during training across 10 epochs. Training and validation accuracies achieved a final validation accuracy of 94.65%.The loss curve demonstrates rapid convergence, with the loss stabilizing near zero by the end of the training. Figure (b) illustrates the training progress of inception resnet v2, showing a validation accuracy of 96.28% and smooth convergence of accuracy and loss curves over 10 epochs and 1420 iterations. The results highlight the model's effective learning and strong generalization, with stable optimization achieved using a constant learning rate of 0.001 on a single CPU. Figure (c)



a) MobileNet v2

b) Inception ResNet v1

c) Custom CNN

Figure 8: Training Progress for Depression vs. Controls Classification (AIIMS, India)

demonstrate the validation accuracy increases steadily and closely follows the training accuracy, indicating low overfitting. The loss curve decreases smoothly, showing effective convergence of the optimization process. The training and validation curves demonstrate a well-trained model with minimal overfitting. High validation accuracy (98.06%) suggests that the model generalizes well to unseen data. The constant learning rate and choice of epochs appear suitable, as the model has converged without unnecessary overtraining.

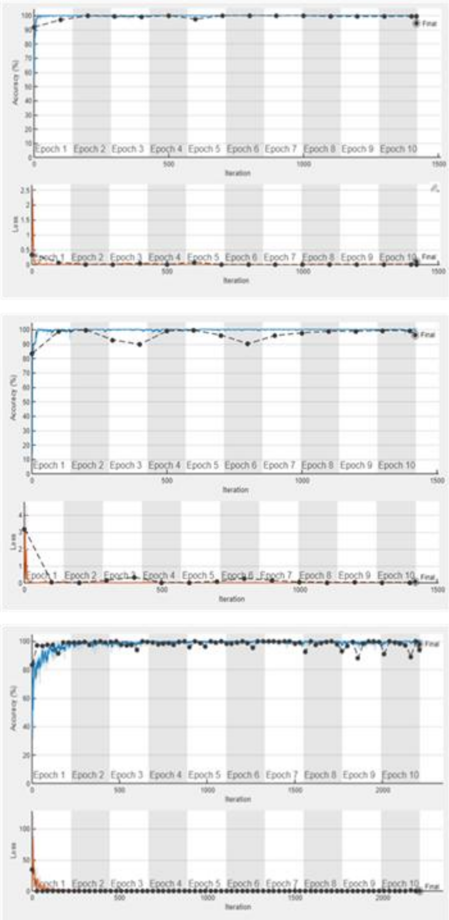
C. Performance Evaluation

The results of the three deep neural networks (custom CNN, MobileNetV2, and InceptionResNetV1) are summarized in

Tables 3 and 4. The performance comparison graph is also depicted in Fig. 10

Network	Accuracy (%)	Specificity (%)	Sensitivity (%)	Recall (%)	F1 Score
Custom CNN	97.29	96.5	98.1	98.1	97.7
MobileNetV2	89.14	92.2	94.6	94.6	93.4
InceptionResNetV1	95.38	94.0	96.4	96.4	95.2

Table III: Performance Metrics for Depression vs. Controls Classification (AIIMS, India)



a) MobileNet v2

b) Inception ResNet v1

c) Custom CNN

Figure 9: Training Progress for Alzheimer's vs. Controls Classification (ADNI)

Network	Accuracy (%)	Specificity (%)	Sensitivity (%)	Recall (%)	F1 Score
Custom CNN	98.06	97.5	98.6	98.6	98.1
MobileNetV2	94.65	93.7	95.9	95.9	94.8
InceptionResNetV1	96.28	94.9	97.1	97.1	96.0

Table IV: : Performance Metrics for Depression vs. Controls Classification (ADNI)

D. Discussion

The results indicate that the custom CNN outperforms both MobileNetV2 and InceptionResNetV1 from an accuracy standpoint for both classification tasks. Notably, the tailored CNN attains an accuracy rate of 97.29% for the depression vs. controls classification using the AIIMS dataset and 98.06% for the Alzheimer's Disease vs. controls classification using the ADNI dataset. This demonstrates the efficacy of the custom CNN architecture tailored to the specific characteristics of the datasets used.

The performance metrics across all networks also highlight the high specificity and sensitivity of the custom CNN, contributing to its superior overall accuracy. The F1 score, which considers both precision and recall, further supports the robustness of the custom CNN in classifying both depression and Alzheimer's Disease from controls.

Overall, the custom CNN provides a significant improvement in classification performance, suggesting its potential for clinical application in distinguishing between healthy individuals and those affected by depression or Alzheimer's Disease.

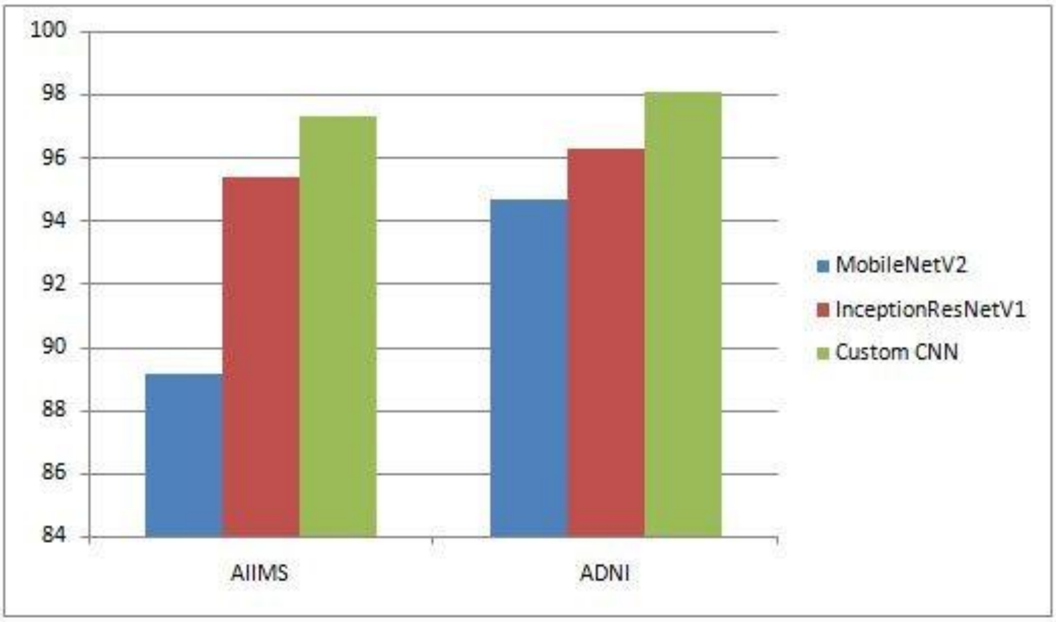


Figure 10: Performance Comparison

E. Comparison with existing literature

Tables 5 and 6 compare the proposed work with existing studies for predicting depression and Alzheimer's subjects using machine learning models. These tables highlight the classification performance of various studies, considering different classifiers and sample sizes.

Sr. No.	Technique	Year	Algorithm Used	Accuracy
1	Zhang et al. [51]	2024	STANet integrates CNN and RNN for depression diagnosis.	82.38 %
2	Hatami et al. [15]	2024	MobileNet V2 model	97.7 % (F1-Score)
3	Dai et al. [8]	2024	Residual Denoising Autoencoder framework for classification.	75.1 %
4	Zhu et al. [54]	2023	Deep graph convolutional neural network	72.1 %
5	Zheng et al. [53]	2023	Function and structure co-attention fusion (FSCF) module	75.2 %
6	Hao et al. [16]	2024	Support Vector Machines (SVMs)	92.9 %
7	Li et al. [24]	2022	Deep convolutional networks for feature extraction and classification	87.46 %
8	Pitsik et al. [33]	2023	Graph neural network (GNN)	93 %
9	Gao et al. [12]	2022	Attention-guided unified deep convolutional neural network	76.54 %
10	Proposed	2024	Custom CNN for classification	97.29 %

Table V: Comparison of Different Techniques for Depression Classification

V. CONCLUSION

This paper outlines a fresh perspective to multiclass classification of depression, Alzheimer's, and control subjects by utilizing deep learning methods. By leveraging a custom convolutional neural network (CNN) alongside two pretrained models, we achieved superior performance in distinguishing these classes from fMRI data. The custom CNN demonstrated particularly high accuracy, achieving 97.29% for the AIIMS dataset (depression vs. controls) and 98.06% for the ADNI dataset (Alzheimer's vs. controls). These findings emphasize the effectiveness of our model in identifying and learning from intricate patterns in grayscale fMRI images. All deep learning programming was conducted using MATLAB 2023a, ensuring a robust and

Sr. No.	Technique	Year	Algorithm Used	Accuracy
1	Ravi et al. [36]	2024	ResNet-50v2	97.84 %
2	Hassan et al. [14]	2024	Random Forest, SVM, and KNN classifiers.	84 %
3	Tajammal et al. [45]	2023	VGG-16, ResNet-18, AlexNet, and Custom CNN.	96.8 %
4	Alrof et al. [2]	2022	Stacked Sparse Autoencoders and Brain Connectivity Graph CN	84.03 %
5	Mohtasib et al. [28]	2022	Logistic-Regression and Random-Forest	74 %
6	Amini et al. [4]	2021	CNN	96.7 %
7	Zamini et al. [50]	2022	Multi-layer Perceptron Artificial Neural Network (ANN)	94.55 %
8	Kavitha et al. [20]	2022	Decision Tree, SVM, Gradient Boost, Random Forest	83 %
9	Wang et al. [47]	2021	3DShuffleNet	85.2 %
10	Parmar et al. [31]	2020	modified 3D CNN	98 %
11	Proposed	2024	Custom CNN	98.06 %

Table VI: Comparison of Different Techniques for Alzheimer's Classification

reproducible implementation of the proposed models. The detailed hyperparameter settings and training configurations provided a clear framework for replicating and extending this work. This research highlights the promise of deep learning methods, especially customized CNNs, in the accurate classification of neurological conditions using fMRI data. The high performance of our models suggests their applicability in clinical settings, potentially aiding in the early identification and distinction between depression and Alzheimer's disease. Future work will explore further optimization of the network architecture and the inclusion of additional datasets to enhance model robustness and applicability.

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