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ADDNet - An Enhanced Convolutional Neural Network for Detection and Classification of Alzheimer's Disease

Radhakrishna Chamakuri[1*], and Dr. Hyma Janapana[2]

[1*]Research Scholar, Department of Computer Science Engineering, GITAM School of Technology, Visakhapatnam, Andhra Pradesh, India. radhakrishnach@gmail.com, https://orcid.org/0009-0005-1682-7947

[2]Associate Professor, Department of Computer Science Engineering, GITAM School of Technology, Visakhapatnam, Andhra Pradesh, India. hjanapan@gitam.edu, https://orcid.org/0000-0002-3643-3946

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Abstract

The World Health Organization (WHO) reports that Alzheimer's disease (AD) is the principal factor that causes dementia, diminishing cognitive abilities of people across the globe. Early detection of Alzheimer's disease (AD) using non-invasive methods is critical for long-term human health. Health and wellbeing for all is one of the sustainable development goals set by the United Nations (UN). In line with this goal, there has been a significant research effort in the healthcare domain to detect Alzheimer's disease. Methodologies based on learning for automatic diagnosis of Alzheimer's disease (AD) have increased in significance with the development of artificial intelligence (AI), machine learning (ML), and deep learning (DL). Existing AI-enabled methods for medical image processing modalities such as magnetic resonance imaging (MRI) are efficient because they are based on profound understanding techniques like convolutional neural networks (CNN). Motivated by this, our investigation on CNN-based methods revealed that there is a need for leveraging network efficiency with the configuration of layers and optimizations. At the end of this research, we provide a system that can automatically detect and classify AD. The framework is based on a deep knowledge of how to detect AD in a given patient using a magnetic resonance imaging (MRI) image. The proposed CNN model, known as Alzheimer's Disease Detection Net (ADDNet), enhances the baseline CNN model. This model has improved the architecture for progressive generation of characteristics and enhanced it for early AD detection. The suggested method, called learning-based Alzheimer's disease detection (LbADD), makes use of ADDNet. We conducted our empirical research using the frequently used Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset as a benchmark. The results of our experiments demonstrate that ADDNet clearly demonstrates its robustness, as it achieves an overall accuracy of 98.83%, which is superior to that of other models. The Clinical Decision Support System (CDSS) can incorporate our approach in healthcare units to assist doctors in AD detection, diagnosis, and correlation of facts.

Keywords: AD Diagnosis, Artificial Intelligence, DL, Convolutional Neural Network.

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*Corresponding author: Research Scholar, Department of Computer Science Engineering, GITAM School of Technology, Visakhapatnam, Andhra Pradesh, India.

1 Introduction

Alzheimer’s disease (AD) is a neurodegenerative disorder caused by brain impairment, leading to progressive memory loss and cognitive decline, severely affecting individuals' daily lives. Early diagnosis is crucial, as it allows for timely medical interventions that can help manage symptoms and slow disease progression. With advancements in artificial intelligence (AI), machine learning (ML), and deep learning (DL), it has become easier to develop models capable of automatically detecting Alzheimer’s from medical data, such as imaging scans (Bangyal et al., 2022; Puente-Castro et al., 2020).

Several learning-based approaches for AD detection have been explored, including transfer learning, which leverages pre-trained models to classify AD using medical images (Puente-Castro et al., 2020). It is common practice to use deep learning models for tasks of this nature. Some examples of these models include convolutional neural networks (CNNs) and long short-term memory (LSTM) networks (Ramzan et al., 2020). CNNs, in particular, are extensively used for image processing tasks, including AD detection via magnetic resonance imaging (MRI) or functional MRI (fMRI) data (Puente-Castro et al., 2020; Li et al., 2020; Janghel & Rathore, 2021). Pretrained models like VGG (Janghel & Rathore, 2021), AlexNet (Nawaz et al., 2021), Xception (Tufail et al., 2020), and ResNet (Balaji et al., 2023) are widely applied in this domain for feature extraction and classification tasks.

For Alzheimer's disease research, MRI and functional MRI (fMRI) are among the most frequently used input images (Li et al., 2020; Janghel & Rathore, 2021), as they provide detailed brain structure and activity data. The Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset (Alzheimer’s Disease Neuroimaging Initiative, n.d.) is a benchmark dataset often employed in AD research. It offers extensive brain MRI information, aiding in the creation and assessment of machine learning models designed for diagnosing AD (Suganya & Rajan, 2022).

The growing body of research in AD detection using AI and ML continues to explore and improve on these techniques, aiming for higher diagnostic accuracy and earlier detection, which is critical for effective treatment and care management

Comprehensive training in the integrated analysis of clinical details, magnetic resonance imaging (MRI), and single nucleotide polymorphisms (SNPs) for the purpose of Alzheimer’s disease (AD), mild cognitive impairment (MCI), and cognitively normal (CN) categorization. The results demonstrate that multi-modality models perform better when it comes to recognizing important features. By providing a holistic view of disease processes and filling in modalities gaps, data integration improves clinical predictions Venugopalan et al., (2021). We find that CNN architectures work well for binary classifications and multi-class AD stage classifications. Two approaches use transfer learning with VGG19 and basic CNNs for 2-D and 3-D scans (Helaly et al., 2022). A web software for Alzheimer's disease allows for remote testing, and it has shown encouraging accuracy rates (Helaly et al., 2022). It turns out that 3D deep convolutional neural networks (CNNs) operate rather well for identifying moderate Alzheimer's, superior to a model based on volume and thickness. Compared to other methods, it finds biomarkers for early Alzheimer's detection more quickly and can predict the disease's course (Toğaçar et al., 2021).

Research indicates that current AI-enabled approaches based on DL techniques like convolutional neural networks excel in handling medical image processing using modalities like MRI. Because of this, our proposed research involved exploring the existing CNN-based solutions and found that it was necessary to optimize and configure the network models to improve efficiency and accuracy of the models.

1.1. Research Contribution

In this research, we present a novel approach for the automatic detection and categorization of Alzheimer's disease (AD) through deep learning techniques. By utilizing MRI scans, the framework is designed to improve early diagnosis by detecting changes in brain structure that are indicative of Alzheimer's progression. Our primary contributions to this study are summarized as follows:

1. We have developed a deep learning-based technique to automatically identify and categorize Alzheimer's disease (AD) through MRI scans.
2. The proposed CNN variant is known as Alzheimer's Disease Detection Net (ADDNet) because it improves the baseline CNN model. This model enhances the architecture for progressive feature generation and optimizes it for early AD detection.
3. The proposed approach, Learning-based AD Detection (LbADD), utilizes ADDNet to automatically detect AD.

The remaining sections of the paper follow this structure. Section 2 investigates the use of deep learning techniques to identify earlier AD. Section 3 presents materials and methods, including the proposed CNN variant named ADDNet. Section 4 displays the experiment results. Section 5 finally closes our work and presents avenues for further investigation.

2 Related Works

This segment examines earlier deep learning models used for AD detection. Bangyal et al., (2022) focused on disease-specific ontologies that facilitate information exchange across fields. With an emphasis on early detection using machine learning, it focuses on AD. A deep learning-driven convolution network achieves 94.61% accuracy, outperforming traditional methods. Ontology construction relying on disease ontology enhances robustness. The study advocates for future evaluations on diverse datasets and real-time diagnostic models. Puente-Castro et al., (2020) introduced a DL-based technique employing sagittal magnetic resonance imaging, proving efficacy comparable to traditional horizontal MRI. Transfer learning enhances accuracy, especially in early-stage detection. Future efforts aim to refine predictions by combining sagittal and frontal plane information. Noor et al., (2020) explored cutting-edge MRI scans, aided by ML, to reveal brain disorders. Comparative analysis favours the convolutional neural network in detecting Parkinson's, schizophrenia, and Alzheimer's. There is a discussion of the challenges and potential solutions. Li et al., (2020) proposed a 4-D DL model (C3d-LSTM) for Alzheimer’s diagnosis using fMRI details, outperforming methods that transform 4D data. Utilizing spatial-temporal information significantly improves AD detection.

Through testing, El-Sappagh et al., (2020) achieved cutting-edge performance by proposing a robust ensemble deep learning model that makes use of background knowledge and multimodal time series data for early Alzheimer's disease prediction. Murugan et al., (2021) suggested the Convolutional Neural Network (CNN) version DEMNET, which can accurately detect the different stages of AD using MRI data with 95.23%, which is better than current methods. Future plans include diverse dataset testing and model enhancement. Janghel & Rathore, (2021) aimed to enhance Alzheimer's Disease (AD) detection accuracy. A method of deep learning that makes use of VGG-16 achieves higher accuracy on fMRI data, outperforming various classifiers. Future work may focus on reducing execution time. Nawaz et al., (2021) explored a diagnosis approach that uses computers to help identify Alzheimer's early on. Transfer learning from a pre-trained AlexNet yields deep features, achieving a higher level of accuracy and outperforming existing methods for multiclass classification. Zhang et al., (2021) describe a new way

for an attention mechanism in a tightly linked convolutional neural network to find and predict Alzheimer's disease from MR images very well, with a high success rate.

Tufail et al., (2020) proposed deep 2D CNNs, including Inception and Xception, for employing structural MRI to diagnose Alzheimer's disease. Transfer learning enhances performance, suggesting effectiveness. Future work involves exploring diverse datasets and modalities. An et al., (2020) compared with six other approaches and offered a deep ensemble learning architecture for Alzheimer's illness classification. It provides an evidence-based approach to better primary care. Mehmood et al., (2021) employed layer-wise transfer learning and tissue segmentation in MRI for early Alzheimer's detection. The proposed model surpasses existing models in testing accuracy. Sathiyamoorthi et al., (2021) presented an innovative algorithm-based computer-aided diagnostic (CAD) method to diagnose Alzheimer's disease, which lifts up the precision and efficacy of diagnosis. Zhang et al., (2021) developed a unique multiclass classification system based on multimodal neuroimaging that uses identification of Alzheimer's disease by feature fusion and selection. The approach shows promising performance in extensive comparison experiments.

Gao & Lima, (2022) looked into how biomarkers can be used with deep learning to diagnose AD using CNN and other feature extraction and classification methods, pointing out problems and suggesting ways to solve them. Chen & Xia, (2021) looked into the ISDL model, which uses deep learning and sparse regression to accurately diagnose AD and MCI, which is better than current methods. Shukla et al., (2023) observed that various diagnostic methods for Alzheimer's disease (AD) consist of robotic processes, artificial intelligence, and biomarker methods, with structural MRI proving vital (Mumtaj Begum, 2022). Fusion-based approaches enhance accuracy, emphasizing deep learning. Saleem et al., (2022) believe that millions of individuals have Alzheimer's disease (AD), which is a serious health hazard (Malathi et al., 2024; Odilov et al., 2024). Deep learning (DL) methods, especially CNN, show promise in AD diagnosis. Challenges like overfitting persist, requiring further attention. Lin et al., (2021) reviewed deep learning's pivotal role in anticipating Alzheimer's disease (AD) through neuroimaging and genomics, highlighting challenges and future directions for research.

Arafa et al., (2022) focused on recent studies using DL to identify AD early and span imaging phases prior to processing and classification challenges. Pirrone et al., (2022) introduced a novel EEG signal analysis method for dementia detection, achieving high accuracy in distinguishing AD, MCI, and HC subjects. The suggested technique offers simplicity and efficiency for potential real-time use. The feature extraction method explores frequency imbalances, demonstrating validity. Future work aims to refine the classification method and test diverse EEG recording protocols for broader applications. The study highlights EEG's potential for early AD diagnosis, suggesting implementation on embedded devices for real-time usage (Veera Boopathy et al., 2024). The proposed method's simplicity and robustness make it suitable for low-cost, portable applications. Tong *et al*. Venugopalan et al., (2021) employed deep learning to integrally analyse MRI, SNPs, and clinical data for AD, MCI, and CN classification. Results show superior performance in multi-modality models, identifying key features. Data integration enhances clinical predictions, offering a comprehensive understanding of disease processes and bridging gaps in modalities (Alamer et al., 2023). The proposed method considers feature-level and decision-level combinations, showcasing significant improvements in model performance.

Helaly et al., (2022) proposed the E2AD2C framework, which uses CNN architectures for binary and multi-class AD classifications. Two methods involve simple CNNs for 2-D and 3-D scans, as well as transfer learning using VGG19. An Alzheimer's web app facilitates remote checking, achieving promising accuracy. Future plans include applying other pre-trained models, dataset augmentation, DCGAN, and MRI segmentation for enhanced AD features. Bari Antor et al., (2021) addressed

Alzheimer's disease, a major concern affecting 45 million people. They applied machine learning models, particularly SVM, to the OASIS dataset for dementia detection. Fine-tuning improved SVM accuracy, making it a reliable tool for early detection and treatment.

Table 1: Summary of Literature Findings

Reference	Approach	Technique	Algorithm	Dataset	Limitations
(Puente-Castro et al., 2020)	Transfer learning	DL techniques	-	OASIS and ADNI	Volumes of sagittal MRI are yet to be explored.
(Murugan et al., 2021)	DL	CNN	CNN based optimization	ADNI	Dataset diversity is to be explored in the future.
(Zhang et al., 2021)	Multiple kernel learning	DL	MKL Multimodal iteration algorithm	ADNI	Method optimization is required.
(Gao & Lima, 2022)	DL	DL techniques	DL based classification	ADNI, OASIS, AIBL	In the future, authors intend to improve DL models further.
(Shukla et al., 2023)	Multi-modality approaches	ML and DL	Multi-fusion algorithm	ADNI	Exploring hybrid DL models is to be done in the future.
(Arafa et al., 2022)	DL	CNN	CNN based algorithm	ADNI and OASIS	CNN and transfer learning are to be combined in the future.
(Helaly et al., 2022)	DL	CNN	Adam optimization algorithm	ADNI	Pre-trained DL models are to be explored.
(Balaji et al., 2023)	DL	CNN	LSTM based algorithm	Custom dataset	Enhancing CNN is desired for further improvement.
(Ebrahimi et al., 2021)	Hybrid	CNN+RNN	Backpropagation learning algorithm	ImageNet	Weights are to be used from pre-trained models in the future.
(Katabathula et al., 2021)	DL	CNN	-	ADNI	End-to-end DL with optimizations is desired in the future.

Balaji et al., (2023) addressed Alzheimer's disease's neurodegenerative aspects, proposing a hybrid deep learning approach with a higher accuracy for early detection. Buvaneswari & Gayathri, (2021) demonstrated a 95% accurate SegNet deep learning-based method for dividing brain MRI images, as well as a ResNet-101 deep learning-based method for classifying AD. Liu et al., (2022) created a deep convolutional neural network (CNN) in three dimensions. The network accurately diagnoses mild Alzheimer's, outperforming a volume/thickness model. It's faster, forecasts progression, and detects biomarkers for early Alzheimer's detection. Chang et al., (2021) explored machine learning that enhances Alzheimer's disease (AD) diagnosis with novel biomarkers, improving sensitivity and specificity and enabling cost-effective outpatient clinic use. Ebrahimi et al., (2021) presented deep sequence-based models that outperform 2D CNNs on 3D MRI volumes for AD detection. With ResNet-18 + LSTM, accuracy was 84%. With a huge accuracy, TCN models outperformed slice-based and voxel-based techniques, indicating potential gains for video processing applications.

To sort AD, Katabathula et al., (2021) used a 3D convolutional network called DenseCNN2 to put together hippocampal segments and global form representations. Verified against other techniques, DenseCNN2 enhances classification performance. In the future, efforts will focus on creating reliable segmentation algorithms, investigating multi-modal prediction models, streamlining pre-processing through end-to-end deep learning, and growing datasets for generalizability testing.

The literature review shows how well existing AI-enabled methods have relied on DL techniques, like convolutional neural networks (CNN), work for processing medical images from MRI and other imaging techniques. The information that is presented in Section 3 pertains to our suggested framework and model, which is intended to address some of the limits and difficulties that are pointed out in Table 1.

3 Materials and Methods

A methodology is proposed for early identification of AD in MRI images using a DL approach. Since convolutional neural networks (CNN) is found to be suitable for processing the medical images, in this research, a CNN-based deep learning model is preferred.

3.1. Problem Definition

Provided brain MRI image of a patient, offering a CNN model upgrade and deep learning framework for probability identification that is done automatically of AD for given patient is the challenging problem considered.

3.2. Proposed Framework

Figure 1 displays the proposed architecture, which automatically detects AD. This framework provides an overview of the approach that is being presented, including its operation as a whole. However, to maximize detection accuracy, we can further enhance it by utilizing instance normalization, region of interest detection, CNN expansion, and patient age information.

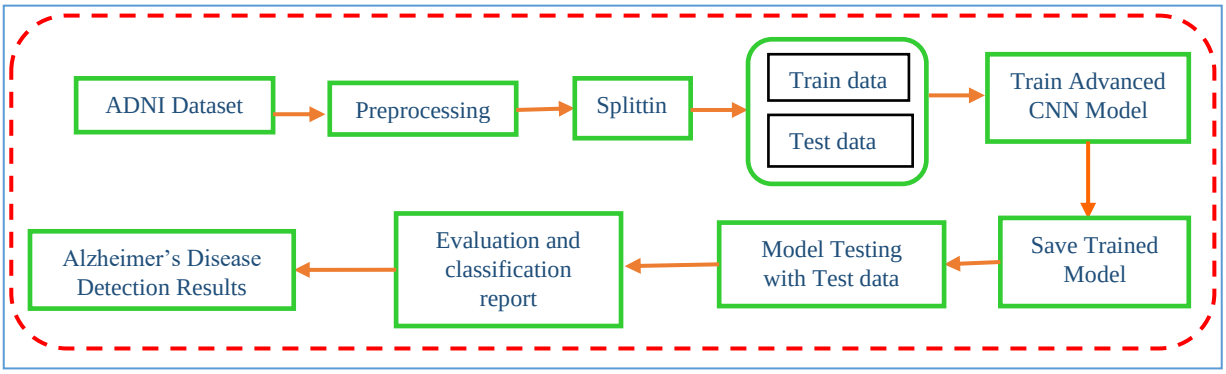

Figure 1: Proposed Deep Learning Framework for AD Detection

Exploratory data analysis (EDA) is used to do preprocessing the ADNI dataset (Alzheimer's Disease Neuroimaging Initiative, n.d.). The ADNI data set is a collection of longitudinal clinical, imaging, genetic, and other biomarker data that represents a comprehensive and widely utilized collection of information. There are several different types of data that are included in it, including related to structure, functional, and molecular brain imaging, as well as biofluid biomarkers, cognitive tests, genetic data, and demographic details. A Schedule of Events (SOE) assigns ADNI participants based on a variety of factors, including their clinical diagnosis (unimpaired, MCI, AD/dementia). The SOE determines the data collected during each visit. The SOE grants access to this information to approved researchers.

Following that, we separate the data into two distinct sets: 20% for testing and 80% for training. More advanced CNN models construct knowledge models from training data and store them for later use. Once saved, the model uses test data to make a prediction about AD. In conclusion, we evaluate the effectiveness of the proposed system and provide a description of our findings.

3.3. Pre-processing

The proposed framework designs preprocessing to enhance the training samples. The optical equipment's insufficient brightness causes MRI pictures to decrease throughout the data collection

process, even with minimal variance. Image improvement techniques often resolve this issue by enhancing or correcting the pixel distribution across a broad spectrum of intensities, thereby improving MRI scans. First, we use picture normalization to reduce machine and impulse noise and modify the image's pixel intensity values. To normalize the picture, we expanded the pixel values to [-1,1] by multiplying them by a factor of 0/255.

Rescaling layer: The rescaling step is essential, especially for image data. Images usually have pixel intensities ranging from 0 to 255, but models like CNNs are sensitive to scale differences. Scaling the values between 0 and 1 ensures that the model operates in a uniform space, leading to better performance. This layer normalizes pixel values from the range [0,255] [0, 255] [0,255] to [0,1] [0, 1] [0,1]. Normalizing input data often enhances the efficiency of DL models, facilitating faster convergence during training and enhancing the stability of the gradient descent process.

$$\widehat{IN} = \left(1 - \hat{I}_{Min}^{T}\right) + \frac{\hat{I}_{Max}^{T} - \hat{I}_{Min}^{T}}{Max - Min} \hat{I}_{Min}^{T} \qquad (1)$$

In the above equation 1, I and $\widehat{IN}$ stand for the regularised brain image and input, respectively, and Min and Max are denoted by 0 and 255 indicates the given brain picture's pixel intensity range. The intensity range of the normalized image is shown by $\hat{I}_{Max}^{T}$ and $\hat{I}_{Min}^{T}$.

After normalization, we reduce the grayscale pictures to 128 x 128 pixels to conform to the input layer dimensions of the previously trained model. The pictures were grayscale; thus, triple-copying the pixel data produced extra channels. A more generalized model and prevention of model overfitting are the goals of using additional training data in a DL model in order to ensure its reliability. That being said, privacy problems make access to huge databases problematic for medical research (Puente-Castro et al., 2020).

Neuroimaging research has significant challenges, particularly with regard to the abundance of AD scans that are available. Furthermore, a tiny, unbalanced dataset produces overfitting issues, reducing the effectiveness of the model. Data augmentation typically resolves class imbalance and data availability issues.

We used augmentation techniques in our pipeline to create new images from each available MRI picture. Figure 2 displays a selection of images enhanced with data. We experimented with a wide variety of data augmenting techniques, including rotation range of image, zooming to certain scale, and brightness change, in order to improve the performance of the model while it was being trained.

3.4. Model Development

The proposed CNN variant is known as Alzheimer's Disease Detection Net (ADDNet) because it enhances the baseline CNN model. This model, shown in Figure 2, has improved architecture for progressive generation key characteristics and improves them for early AD detection. The enhanced CNN will receive the pre-processed pictures, each with a 128x128 matrix size, for training and testing. An input, several constructed layers, and an output make up the suggested CNN model. In this work, each of the three two-dimensional (2D) convolution sheets contained a 2D max pooling layer. Between the input and a kernel also known as a filter that serves as a method identifier conv functions linearly. The filters, trained to extract specific information from a picture, have a limited field of application. The term "convolution layer" has the following definition:

$$X_n^r = \alpha\left(\sum_{m=1}^{k} X_m^{r-1} * w_{mn}^r + b_m^r\right) \qquad (2)$$

Where X_m^{r-l} is the n^{th} map for preceding stratum $(r-l)^{th}$, X_n^r is the n^{th} map for current (r^{th}) coating, yet k reflects total number of activation maps in the input in equation 2. The vectors denoted as weight and bias are $w_{mn}^r$and b_m^r. Convolution operations are performed with the * operator, where α stands for the activation function.

The design of the CNN model (ADDNet) includes three convolution layers, utilizing a kernel of size 3x3, and then max pool layers are implemented of a 2x2 kernel. These layers learn higher-level features, such as parts of objects or more complex patterns. As the network goes deeper, it captures increasingly abstract representations of the data. As the model progresses deeper, the model may capture increasingly intricate and abstract patterns as the number of filters rises (from 16 to 64). The network keeps using a 3x3 kernel size in the second and third blocks. After each convolutional layer, a max-pooling layer is implemented to decrease the dimensions (spatial) of image and further consolidate the learned features. Increases in pooling and filter sizes have demonstrated the effectiveness of this type of multilayer structure in a time-series study (Chen & Xia, 2021; Shukla et al., 2023).

The definition of the model's input is $x = x_1, x_2, \ldots . x_n$, while the output sequence is denoted by $y = y_1, y_2, \ldots, y_m$. The cost matrix (xi) was used to alter the network's last layer's output. The loss function is denoted as (L) if y is the output of the single model, and ($\mathbb{C}$) is the intended class, then (∂^i) is the updated result, which looks like thi in equations 3 and 4:

$$\partial^i = \text{ł}\left(\zeta_{\mathbb{C},} y^i\right), : \partial^i{}_{\mathbb{C}} \geq \partial^i{}_j \forall j \neq \mathbb{C} \qquad (3)$$

This is how the loss function is changed:

$$Ł = -\sum_n t_n \log\left(\partial_n\right) \qquad (4)$$

where ∂_n takes into account the cost based on class (ξ) this has to do with the results on $y_n$via the SoftMax function in equation 5 (Saleem et al., 2022):

$$\partial_n = \frac{\xi_{\mathbb{C},n} \exp\left(y_n\right)}{\sum_k \xi_{\mathbb{C},k} \exp\left(y_k\right)} \qquad (5)$$

A class's weight is obtained by the number of specimens it includes. The main aim is of making 1 class p specimen as significant as t test if class η has t samples, even when class η has times more samples than class p. Consequently, p's class weight is t times larger than η's.

Table 2: Proposed ADDNet Model Configurations

Layer	**Convolution**	**Max Pooling**	**Dropout**
1	filters=16, kernel_size = (3,3), padding='Same', activation='relu'	pool_size = (2,2) strides = (2,2)	0.2
2	filters=32, kernel_size = (3,3), padding='Same', activation='relu'	pool_size = (2,2), strides = (2,2)	0.2
3	filters=64, kernel_size = (3,3), padding='Same', activation='relu'	pool_size = (2,2), strides = (2,2)	0.2
Parameter		**Value**	
Size of the batch		32	
Learning Rate		0.001	
Optimizer		'Adam'	
Epochs		30	
Total Parameters		2,121,380	
Trainable Parameters		2,121,380	
Non-Trainable Parameters		NIL	

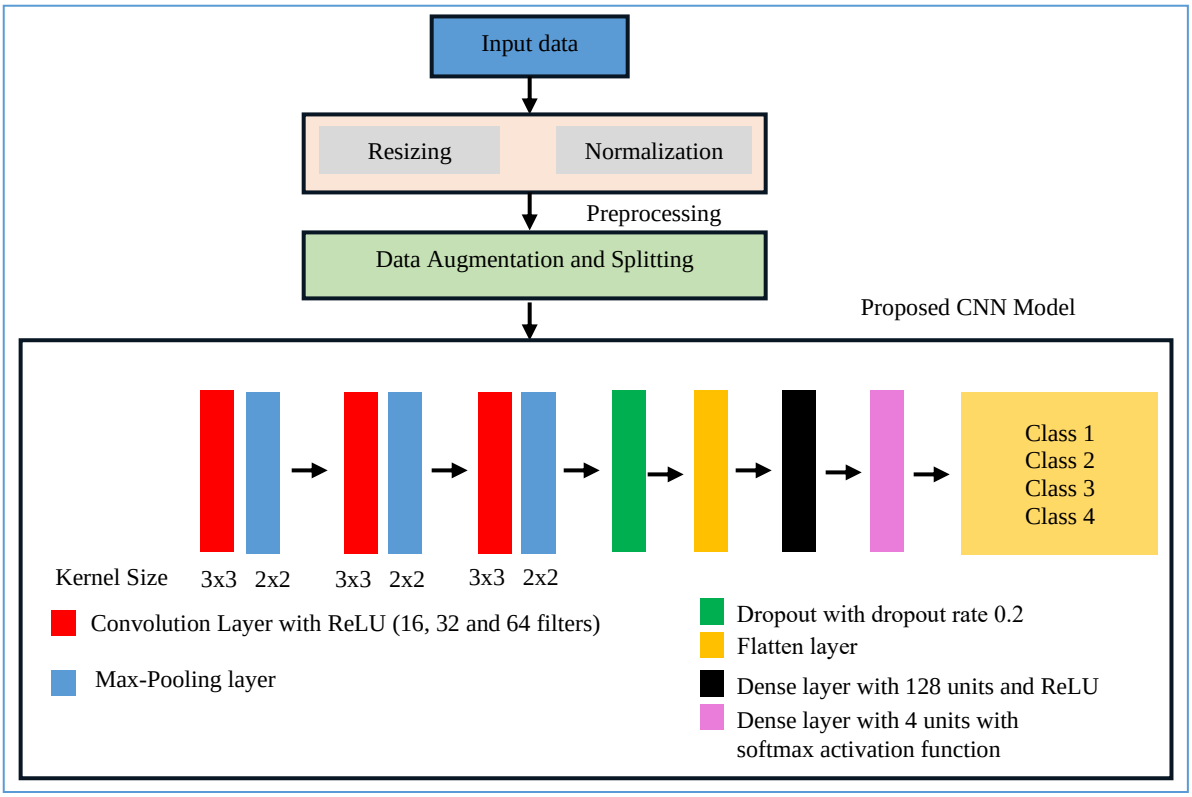

Figure 2: Proposed Deep Learning Model Known as ADDNet based on CNN

3.5. Key Features of the Model Development

Model Architecture of Layer Configuration: As presented in the Figure 2 and Table 2, the convolutional neural network comprises of three convolutional segments, including a kernel size of 3x3 and filters ranging from 16 to 64. Max pooling layers, with a pool size of 2x2 and strides of 2, follow each convolutional layer to reduce the input's spatial dimensions. Fully connected (FC) layers process the results from the convolutional layers, and a final SoftMax layer with four neurons classifies the input into one of four AD-related classes.

Convolution Layer: The main job of the convolution layer is to find basic features in the MRI image, like edges, textures, and simple shapes. These traits are gained by using filters on specific parts of the source image.

Max Pooling Layer: The job of this layer is to reduce the spatial magnitudes, i.e., the dimensions of the feature maps extracted from the convolution layer, but this would preserve the important details of the feature map, and this also helps make the model invariant to small shifts in the input image and reduces computational complexity.

Dropout Layer: Prevents overfitting by randomly "dropping out" (ignoring) a subset of neurons during training. This drives the model to learn duplicate representations of the data, ensuring that it does not rely too much on single neurons. In our architecture, we have set the dropout sets of 20% of the neurons to zero during each training step, making the model more robust and helping it generalize better to unseen data. Overfitting occurs when a model demonstrates high performance on training data while exhibiting low performance on validation or test data. Dropout serves as an effective method to mitigate this effect.

Flatten Layer: Following the convolutional and pooling stages, the features that have been extracted remain in a two-dimensional format. The flatten layer reshapes these multi-dimensional arrays into a single long vector, this is subsequently input into the dense layers. Flattening is necessary for transitioning from feature extraction to classification. Transforms the two-dimensional feature maps into a one-dimensional vector, rendering the data suitable for fully connected layers.

Dense layer (Fully Connected): Performs the finale classification by combining the features that were learned by the convolutional layers prior to performance. This connects every neuron from the previous layer to every neuron in the next, allowing the network to learn highly abstract patterns and combinations of features. In our model, we have used a fully connected layer that has 128 neurons and uses ReLU activation to introduce non-linearity, helping the network learn more complex patterns. It combines the information from all previous layers to produce a meaningful representation for the final classification step.

ReLU (Rectified Linear Unit): A function that activates all convolutional layers. This nonlinear function enables the model to discern intricate patterns from the MRI data.

Dense Layer with SoftMax Activation: This makes sure the values in the output add up to one and form a probability distribution. Each neuron represents the probability that the input be in the right place to a firm class (Alzheimer's stages, for example). The highest likelihood is taken as the predicted class. In our model, since we've used all four classes, the SoftMax function is applied in this layer to produce a probability distribution over the classes.

Loss Function: Measures the degree to which the model's predictions and the actual labels correspond. In this instance, we employ *sparse_categorical_crossentropy*, a widely used technique in multiclass classification. Also, we labelled them as integers (0, 1, 2, or 3), rather than one-hot encoded vectors.

The values are changed in the loss function when the gradient opposite manner with regard to the parameters (i.e., $\nabla\_\odot$ L ($\odot$)) aiming to reduce the loss function L ($\odot$). Each iteration compares the intended and projected outputs, spreading the error backward. Cross-entropy is a commonly employed statistic in performance evaluation. Any optimization strategy's primary goal is to achieve the situation where the expected and desired outputs are identical and the cross-entropy value is close to zero.

The model aims to minimize the loss during training, *sparse_categorical_crossentropy* is suited for multi-class classification when labels are integers. It calculates the difference between the predicted class probabilities and the actual class. As H (p, q) =-$\sum_x p(x)$log ($q(x)$), the categorical-cross entropy can be expressed, where p and q represent the predicted and actual distributions, respectively.

Optimization: Adam modifies the learning rate for every parameter, which leads to more stable training and quicker convergence. It's ideal for deep learning models because of its efficiency in handling sparse gradients and noise. The model uses the 'Adam' optimizer with a learning rate of 0.001, batch size of 32, and training for 30 epochs. We chose Adam because of its adaptive learning rate capabilities, which facilitate faster convergence during training. Adam is a popular optimizer that combines the advantages of two other methods: The two methods are the Adaptive Gradient Algorithm (AdaGrad) and Root Mean square Propagation (RMSProp).

3.6. Dataset Used

The Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset (Alzheimer's Disease Neuroimaging Initiative, n.d.) is a well-established benchmark dataset widely used for research on Alzheimer's disease

detection using brain MRI images. It consists of 6,400 samples of brain MRI images, each with a resolution of 128 x 128 pixels. The dataset is categorized into four unique classes reflecting the stages of dementia progression.

Table 3: Different Class Labels and Data Distribution

Class	Class Description	# Samples	Percentage (%)
1	Mild Demented	896	14
2	Moderate Demented	640	10
3	Non-Demented	3200	50
4	Very Mild Demented	1664	26

There are 6400 samples in the dataset overall. Table 3 shows the four classes of images and their statistics. This class distribution reveals a notable imbalance, with half of the samples representing non-demented cases and the remaining samples split among the dementia categories. Such an imbalance is typical in medical datasets and presents a challenge in building models that generalize well across all classes.

Our study relies on this dataset to validate and evaluate the suggested AD detection model that uses convolutional neural networks (CNNs). In order to address the inherent class imbalance, it is designed to make use of advanced approaches such as dropout and optimization procedures, both of which contribute to accurate classification across all phases of the disease.

3.7. Proposed Algorithm

The model is implemented based on the ADDNet framework by exploiting technique called Learning based AD Detection (LbADD).

Algorithm: Learning based AD Detection (LbADD)
Input: ADNI dataset D
Output: AD detection results R, performance statistics P

1. **Initialization**: Begin the algorithm.
2. **Data Preprocessing**: Perform preprocessing on the dataset D, to obtain processed dataset D'
3. **Data Splitting**: Split the processed dataset D' into a training set $T1$ and test set $T2$.
4. **Model Configuration**: Configure the **ADDNet** model m as per the model specifications
5. **Model Compilation**: Compile the configured model m using a suitable optimization algorithm θ.
6. **Model Training**: Train the compiled model m using the training set $T1$ to minimize the loss function $L(m, T1)$.
7. **Model Saving**: Save the trained model m to a designated storage location for future use.
8. **Model Loading**: Load the saved model m from the storage location.
9. **Model Testing**: Perform inference on the test set $T2$ using the loaded model m to obtain the predicted results R. (R<- *Test (m, T2)*)
10. **Performance Evaluation**: Evaluate the obtained results R against the ground truth labels GT using appropriate evaluation metrics to calculate performance metrics P.
    - Performance Metrics: P=*Evaluate* (R, GT)
11. **Display Results**: Display the predicted results R.
12. **Display Performance Metrics**: Display the calculated performance metrics P.
13. **Termination**: End the algorithm.

Algorithm 1: Learning based AD Detection (LbADD)

The ADNI dataset (Alzheimer's Disease Neuroimaging Initiative, n.d.) serves as input for the Learning based AD Detection (LbADD) algorithm. The preprocessing phase of the provided dataset

entails scaling the images to render them suitable for supervised learning. 80% of the data is designated for training (T1), whereas remaining 20% is allotted for testing (T2). Data augmenting methods such as rotation, flipping, zooming, shearing, and center shifting are employed to enhance model performance during training. The ADDNet model is utilized throughout the training phase. The training data for the enhanced CNN model constitutes 80%. Training data is utilized to instruct the model and acquire discernible knowledge. Transfer learning enables the model to remain available for future application. The trained model is evaluated with unlabelled data. The model generates predictions, resulting in labels indicating the presence or absence of Alzheimer's disease, as well as its classification stage.

3.8. Evaluation Methodology

The confusion matrix is used as the foundation for comparing the evaluation of the proposed algorithm with the state of the art. Various measures included in the assessment procedure are displayed in Table 4.

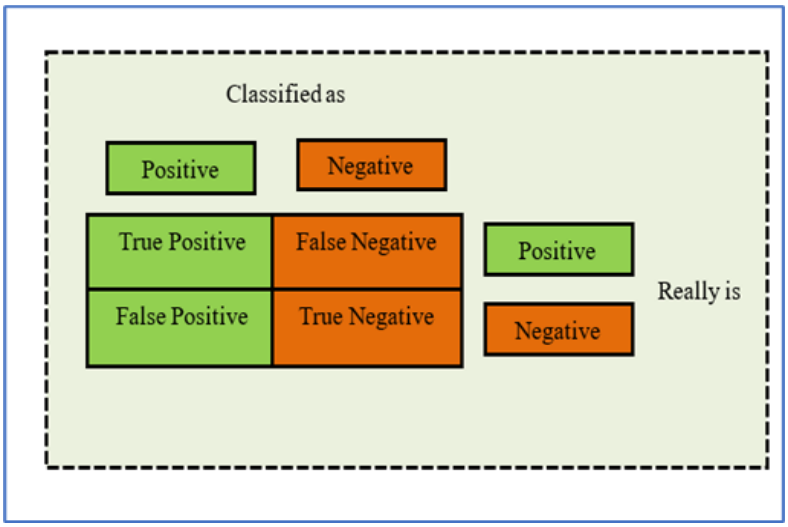

Figure 3: Confusion Matrix

Measures such as true positive (TP), false positive (FP), false negative (FN), and true negative (TN) are displayed in the confusion matrix, which is based on the Figure 3 and Table 4. Their determination involves contrasting the output of the machine learning system with the actual data.

Table 4: Performance Metrics Used for Evaluation

Metric	Formula	Value range	Best Value
Accuracy	$\frac{TP + TN}{TP + TN + FP + FN}$	[0; 1]	1
Precision (p)	$\frac{TP}{TP + FP}$	[0; 1]	1
Recall (r)	$\frac{TP}{TP + FN}$	[0; 1]	1
F1-Score	$2 * \frac{(p * r)}{(p + r)}$	[0; 1]	1

Positive predictive value is associated with accuracy, whereas true positive rate is known as recall. In contrast to accuracy measurements, the F1-score—which is determined by taking the harmonic mean of recall and precision—is a statistic that does not show imbalance.

4 Experimental Results

The findings of this section are shown in experiments made with the implemented prototype. Each of the thirty epochs the proposed ADDNet model is trained for using a batch size of 32. However, early stopping is set to true to enable the framework to stop iterations at the convergence. Adam is the optimizer used, while the loss function used is known as sparse categorical cross entropy. Our model is implemented using Keras and Tensorflow. The model ADDNet is evaluated for its performance and contrasted with cutting-edge models in (Puente-Castro et al., 2020; Helaly et al., 2022; Ebrahimi et al., 2021; Katabathula et al., 2021). The ADNI dataset (Alzheimer's Disease Neuroimaging Initiative, n.d.) is used for our empirical study.

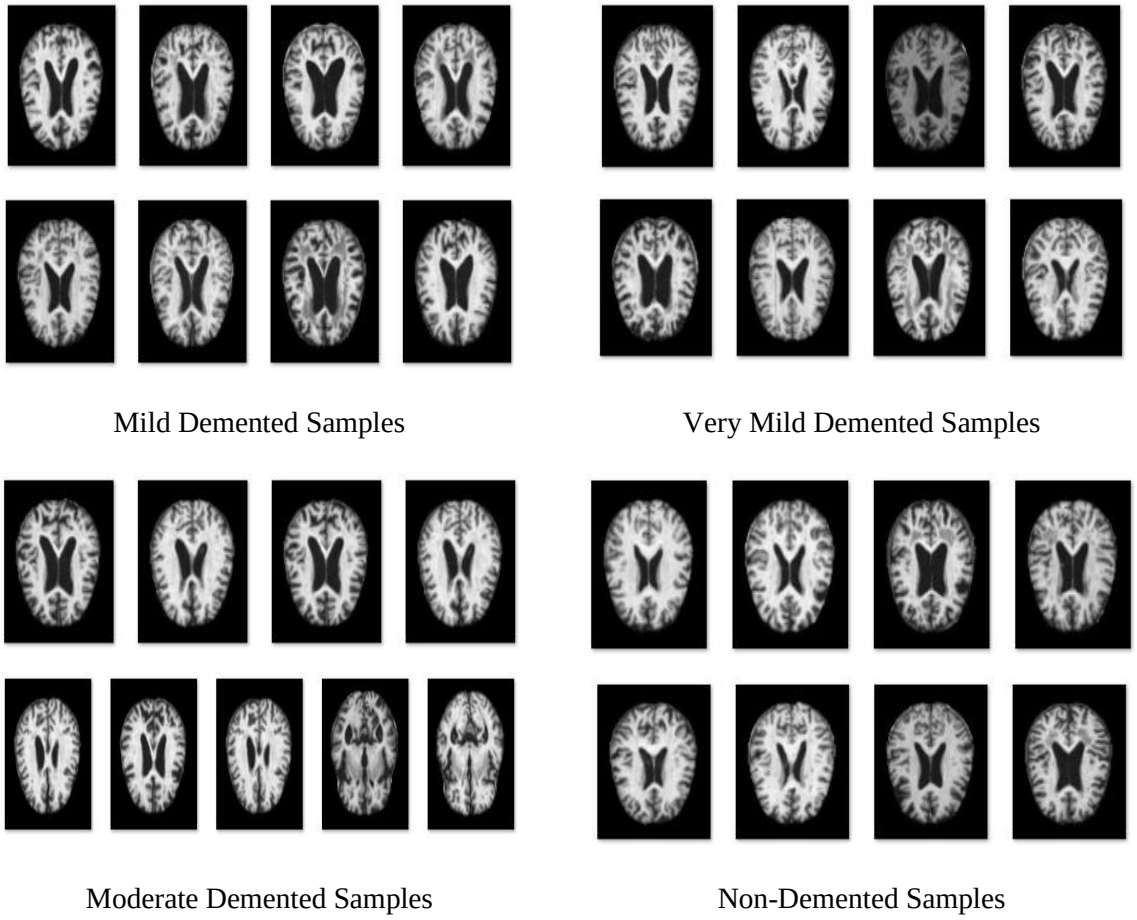

Figure 4: An Excerpt of Brain MRI Images from Dataset

The dataset has four classes of samples as illustrated in Figure 4. Our model supports, therefore, multi-class classification. The experiments are made with the test ADNI data set (Alzheimer's Disease Neuroimaging Initiative, n.d.) which has four classes of samples. The trained model is persisted and reused in our study.

4.1. Results of Binary Classification

Here are the findings from the binary classification used to identify AD. The proposed deep learning model is configured with fully connected layer to discriminate AD cases from normal ones.

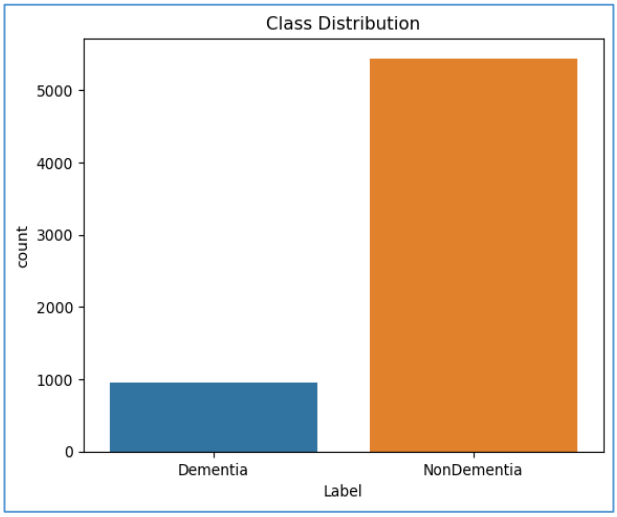

Figure 5: Sample Data Distribution between Dementia and Non-dementia

As presented in Figure 5, the quantity of samples included in the dataset belonging to both class labels such as Dementia and Non-dementia is provided.

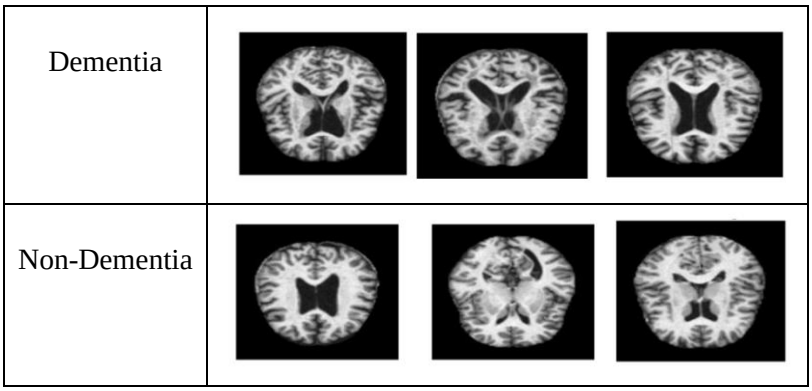

Figure 6: Result of Binary Classification

In the studies, the deep learning network could distinguish between AD and Non-AD data, as shown in Figure 6.

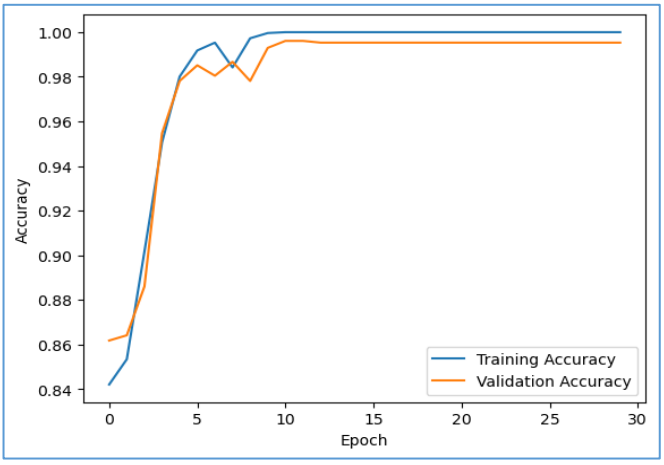

Figure 7: Training and Validation Binary Classification Accuracy

As presented in Figure 7, the accuracy dynamics of binary classification are provided against number of epochs.

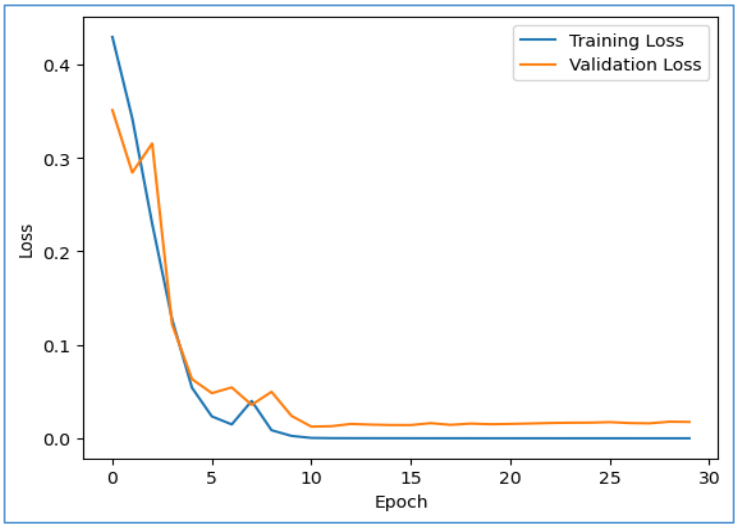

Figure 8: Training and Validation Binary Classification Loss

As presented in Figure 8, the loss dynamics of binary classification are provided against number of epochs.

Table 5: Model Performance with Binary Classification

Measure	**Precision**	**Recall**	**F1-Score**	**Accuracy**
Performance (%)	98.6	98	98.50	98.9

The suggested deep learning model has produced results for binary classification, which are shown in Table 5.

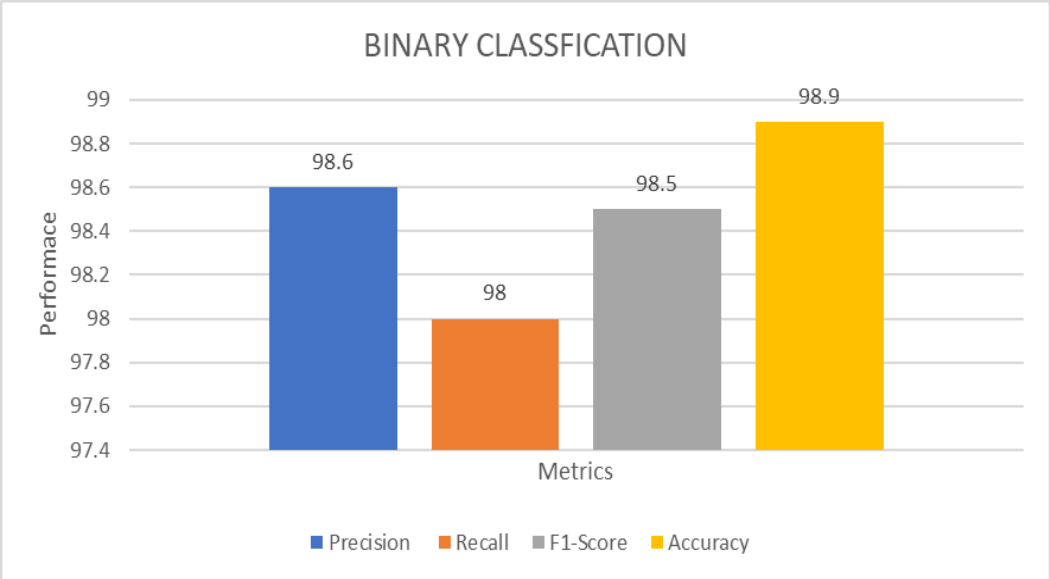

Figure 9: Results of Binary Classification

As presented in Figure 9, the suggested model demonstrated 98.9% accuracy, 98% recall, 98.50% F1-score, and 98.6% precision when utilized for binary classification.

4.2. Results of Multi-class Classification

Since the Alzheimer's detection (AD) is of many categories, it is very important to have multi-class classification to have a more meaningful diagnosis of AD. Such multi-class classification helps healthcare professionals to understand and take care of treatment procedures for patients. Figure 10, depicts the results from the ADDNet model multi class classification of Alzheimer's detection (AD).

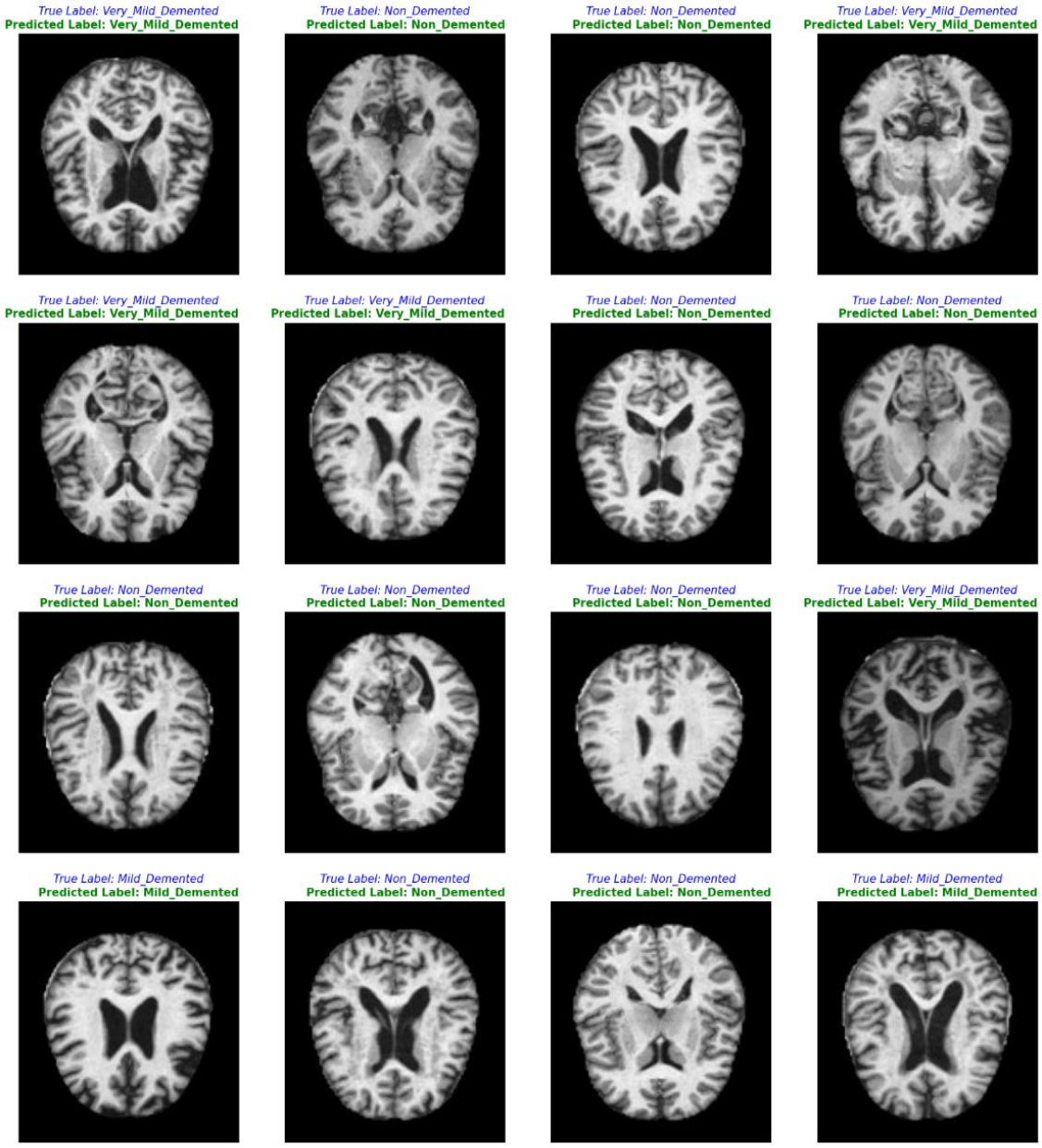

Figure 10: The Test Results Show the True Labels and the Expected Labels for Each Sample

The experimental outcomes are the predicted labels 1, 2, 3, and 4, which, in turn, correspond to the applicable categories of non-demented, moderately demented, slightly demented, and very mildly demented, respectively. The early stopping choice caused the model to converge early even though it only had 30 epochs. The accuracy of the proposed model in relation to the number of epochs is illustrated in Figure 11.

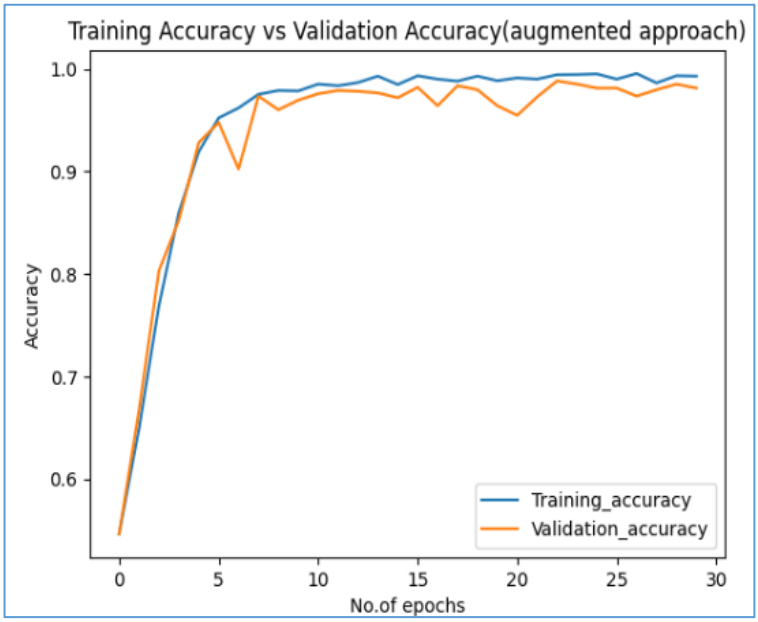

Figure 11: Training and Validation Multi-class Classification Accuracy

Accuracy results for training and validation are contrasted with the total number of epochs. The model's accuracy increases with time as a result of the increasing knowledge it gains from evolving historical periods. The model is converged to highest accuracy at around 30 epochs. Model loss dynamics are presented in Figure 12.

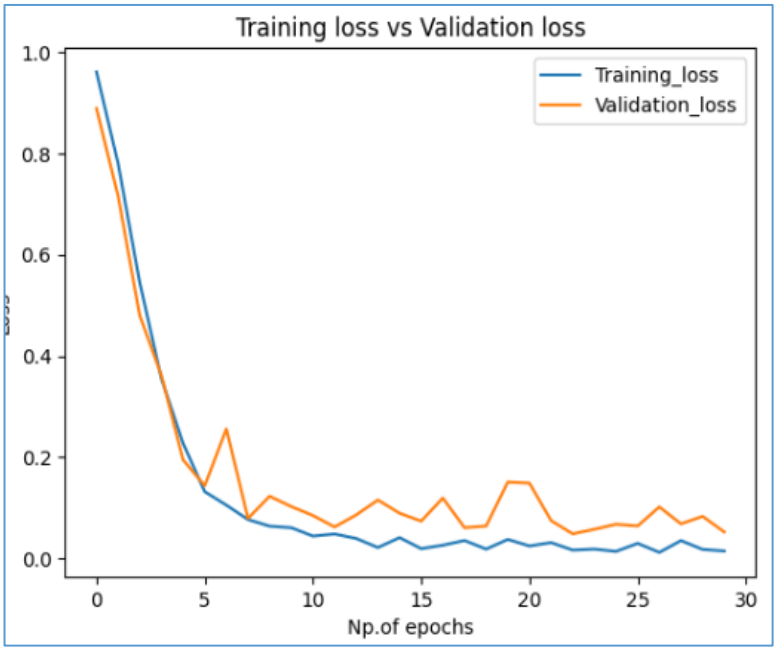

Figure 12: Training and Validation Multi-class Classification Loss

The outcomes of training and validation losses are compared to the number of epochs. As there is progress in epochs, the loss of the model is gradually decreased due to increased knowledge gained by the model. The model is converged to minimal loss at around 30 epochs. Performance of our model ADDNet is presented in Table 6.

Table 6: Performance of ADDNet Model

Measure	Performance (%)
Precision	97.23
Recall	98.54
F-1 Score	97.88
Accuracy	98.83

The proposed model exhibited 97.23% precision, 98.54% recall and 97.88% F1-score. It has achieved 98.83% accuracy. The performance of the suggested model is represented visually in Figure 13.

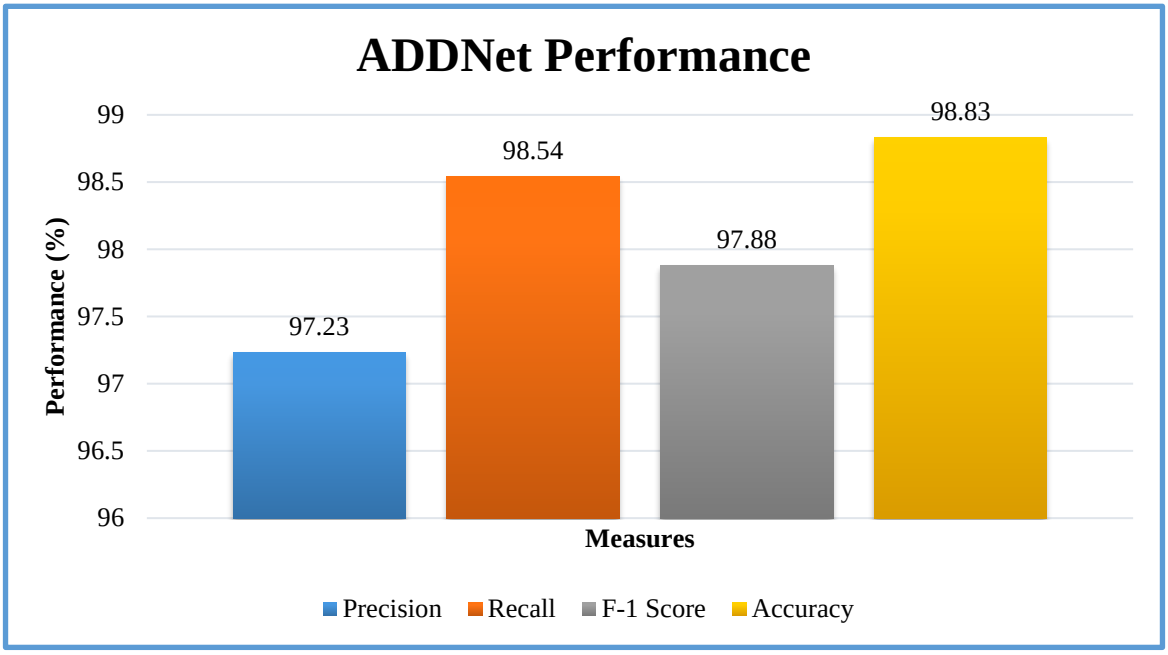

Figure 13: Performance of ADDNet Model in AD Detection and Multi-class Classification

4.3. Performance Consideration and Significance of Metrics

Evaluating the efficacy of any ML or DL model, particularly those used in healthcare, the choice of metrics such as precision, recall, F1-score, and accuracy are very critical. Here are the details about the significance of each metric.

Precision

The proportion of true positives out of all instances the model predicted as positive (i.e., how many of the positive predictions were actually correct).

Contextual Significance: Precision is critical in scenarios where the cost of false positives is high. For example, incorrectly diagnosing a healthy individual with Alzheimer's could lead to unnecessary anxiety and further testing.

Use Case in Alzheimer's Diagnosis: High precision is valuable in ensuring that when the model predicts Alzheimer's (or a certain stage), it's more likely to be correct, avoiding false positives. ADDNet resulted in a 97.23%, which is higher compared to other models.

Recall (Sensitivity or True Positive Rate)

The percentage of true positives among all actual positives, or the number of actual positive instances that the model correctly identified.

Contextual Significance: Recall is especially important in medical diagnostics, where false negatives (i.e., missed diagnoses) can have severe consequences. Failure to identify an early-stage patient in Alzheimer's disease can delay critical interventions.

Use Case in Alzheimer's Diagnosis: Having a high recall guarantees that the model is able to identify the greatest number of actual cases, minimizing the risk of undiagnosed patients progressing without treatment. ADDNet achieved a 98.54% score, which is higher than other models.

F1-Score

The F1-Score is the harmonic mean of precision and recall, balancing the trade-off between them.

Contextual Significance: The F1-score is particularly useful when there is an uneven class distribution or when both false positives and false negatives are costly. It provides a more balanced measure compared to accuracy.

Use Case in Alzheimer's Diagnosis: Given that both false positives and false negatives can have serious consequences in Alzheimer's diagnosis, the F1-score provides a more holistic view of the model's; in our case, ADDNet's F1-score is 97.88%.

Accuracy

The proportion of correctly classified instances out of the total instances.

Contextual Significance: While accuracy gives a general sense of the model’s performance, it can be misleading in cases of class imbalance.

Use Case in Alzheimer's Diagnosis: If the dataset is balanced, accuracy can be a useful metric. However, Alzheimer's stages are often imbalanced, so accuracy alone might not reflect real-world performance. We used the ADNI dataset (Alzheimer’s Disease Neuroimaging Initiative, n.d.), a widely used benchmark dataset for brain MRI-based AD detection research, and our ADDNet model outperforms other models with an accuracy of 98.83%.

4.4. Performance Comparation

Given that the model is built with altered layers and parameters, it is discovered that the suggested model performs better. The following Table 7, compares the performance of the proposed Alzheimer's Disease Detection Network (ADDNet) with state-of-the-art models for Alzheimer's disease (AD) detection based on MRI images. It highlights the accuracy improvements achieved by ADDNet in comparison with previous models:

Table 7: Comparison of ADDNet with State-of-the-art Models

AD Detection Models	Accuracy	Year of publication
Puente-Castro *et al.*	86.81	2020
Ebrahimi *et al.*	91.78	2021
Katabathula *et al.*	92.5	2021
Helaly *et al.*	95.17	2022
ADDNet (Proposed)	**98.83**	**-**

The current methods for comparing findings are CNN-based strategies that may be found in the most recent research. Figure 14 illustrates the efficacy of many deep learning models for AD detection and multi-class categorization.

Accuracy is the primary metric that the comparison of performance of each model. Accuracy that is higher signifies performance that is better. Puente-Castro et al., (2020) uses the ResNet model for feature engineering, while the Support Vector Machine (SVM) is used for classification. When compared to its predecessors, this model is able to attain a performance that is somewhat satisfactory thanks to the hybrid method that integrates both DL and ML approaches. The accuracy of the model that is shown in Puente-Castro et al., (2020) is 86.81%. MRI images from the ADNI dataset were employed by the CNN-based technique that was presented in (Helaly et al., 2022). A substantially better degree of accuracy (95.17%) was achieved by them by optimizing their CNN model, which resulted in a significant improvement over the model in Puente-Castro et al., (2020). Using a deep sequencing process, the detection of AD is carried out in (Ebrahimi et al., 2021). There are CNN and RNN models utilized in the pipeline for the purpose of classification and feature extraction. The accuracy of this model was 91.78%, which is higher than the accuracy rate of Puente-Castro et al., (2020), but lower than the accuracy rate of the model in (Helaly et al., 2022). A dense CNN model is utilized in (Katabathula et al., 2021) for the purpose of AD detection. This particular model consists of two pipelines that are joined together before a layer that is completely connected. 92.50 percent accuracy was achieved by this model.

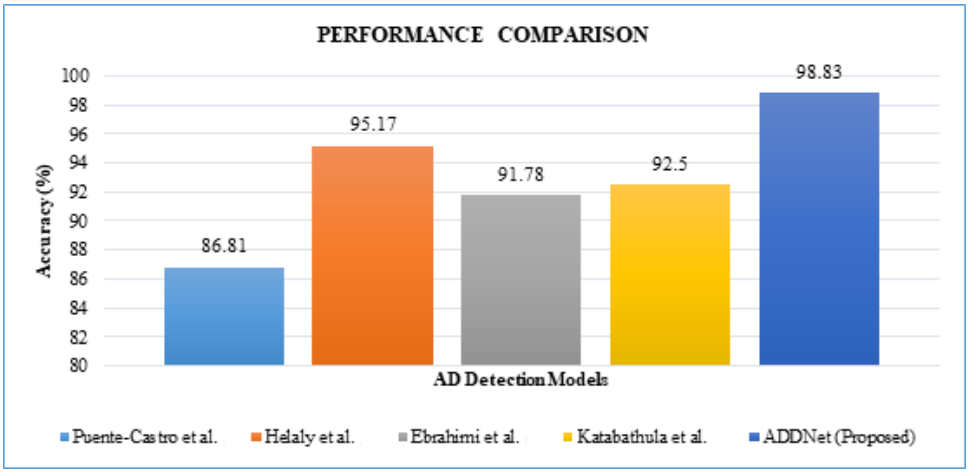

Figure 14: Performance Comparison Among AD Detection Models in Terms of Accuracy

The proposed ADDNet model exceeded all other cutting-edge models, obtaining the highest accuracy i.e. 98.83%. The modification of its architecture and the parameters that were found through empirical research are the reasons for its increased performance in comparison to other state of the art models.

4.5. Real Time Usage and its Consideration

CNN models have demonstrated significant efficacy in detecting AD, predominantly in MRI imageries. These models significantly assist in addressing modern challenges related to disease detection precision. CNN models for Alzheimer's diagnosis exhibit significant precision in detecting AD through MRI and positron emission tomography (PET) scans. These models can detect early indicators of Alzheimer's disease, enabling timely diagnosis, which is essential for swift healthcare intervention. Clinical Decision Support Systems (CDSS) are progressively incorporating models based on Convolutional Neural Networks (CNN). These technologies aid physicians by automating MRI scan analysis and offering diagnostic recommendations.

Our model ADDNet can be integrated with any Clinical Decision Support System (CDSS) to help the health care systems/professionals detect AD or identify the early stages of AD; thus, it would help in reducing the errors in diagnosis and also improve patient care across the health care industries.

Despite the higher accuracy of CNN models, real-world challenges arise when integrating and implementing them in healthcare applications.

1. **Data Accuracy:** Models trained on controlled datasets may exhibit reduced effectiveness on real-world patient data due to variations in imaging equipment, patient demographics, and data quality. Clinical data from real-world environments frequently demonstrate increased variation compared to standardized datasets like ADNI.
2. **Interpretability:** Interpretability is a critical issue due to the inherent "black box" nature of CNN models. Clinicians sometimes seek explanations for the model's predictions. Lack of interpretability may undermine trust and hinder adoption in the healthcare sector.
3. **Regulation and Ethical:** To address regulatory and ethical issues, CNN models must adhere to stringent standards for use in healthcare applications. Models must be safe, dependable, and comply with patient privacy rules for deployment in clinical settings.

Recent developments aim to address these difficulties by improving model transparency through attention processes, strengthening model resilience, and diversifying training datasets to more accurately represent real-world settings. Mitigating these obstacles could significantly improve Alzheimer's disease diagnosis, increasing the accessibility and precision of early detection in standard healthcare protocols.

The application of these models in healthcare demonstrates promise; nonetheless, thorough assessment is essential to translating research findings into viable clinical practices.

5 Conclusion and Future Work

This research presents a framework for the automated identification and categorization of AD. The framework relies on deep learning to acquire knowledge about how to detect AD in a given patient using an MRI image. The proposed CNN variant, known as Alzheimer's Disease Detection Net (ADDNet), enhances the baseline CNN model. This model boasts an improved architecture that facilitates the progressive generation of features and optimizes them for early detection of Alzheimer's disease (AD). These models simplify the distinction between each class's representation, as CNNs identify patterns locally through multiple sliding windows. For the subsequent convolutional layers, we adjusted the dropout layer to 0.2, and for the initial and second convolutional layers, we adjusted the dropout layer to 0.25. Another name for linear rectification is Rectified Linear Unit, or ReLU, which serves as the activation function of every convolutional layer. We propose the learning-based AD detection (LbADD) technique, which leverages ADDNet. We used the widely used ADNI benchmark dataset for our empirical study. Our experimental results show that ADDNet's resilience is evident, with an overall accuracy of 98.83% outperforming existing models. The proposed model has certain limitations. First, the model's evaluation solely relies on the MRI modality, necessitating comparison with other brain image modalities. Second, we test the ADDNet using 2D brain structures, and we plan to improve and evaluate it with 3D modalities as well. Currently, the model lacks support for Region of Interest (ROI) computation, a feature that could potentially enhance its performance. We plan to conduct further research to enhance the model's transparency and interpretability, thereby strengthening its robustness and expanding its application to more training data sets in the future.

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Authors Biography

Radhakrishna Chamakuri, is a research scholar in the Department of Computer Science Engineering at the GITAM School of Technology, GITAM University, Visakhapatnam, Andhra Pradesh, India. He obtained a Bachelor of Technology and Master of Technology in Computer Science from JNTU University, Hyderabad, Telangana. An experienced software engineering leader with over 20 years of leading high-performance software development teams, he is results-oriented. He is skilled at strategic planning, team management, and employing cutting-edge technology to grow and improve operations.

Dr. Hyma Janapana, is an Associate Professor in the Department of Computer Science and Engineering at GITAM School of Technology, GITAM University, Visakhapatnam, Andhra Pradesh, India. She has extensive experience in academia with a continuous improvement in research, teaching, and leadership. Her research interests lie in Data Mining and Machine Learning. A dedicated education professional, she holds a PhD in Computer Science and Engineering from JNTUH College of Engineering, Hyderabad.