Received: 1 January 2024 | *Revised: 14 April 2024* | *Accepted: 26 April 2024*
DOI: 10.37917/ijeee.22.1.43 *Vol. 22 | Issue 1 | June 2026*

Open Access

Iraqi Journal for Electrical and Electronic Engineering
Original Article

IJEEE University of Basrah College of Engineering

Alzheimer's Disease Diagnose using Deep Learning for Brain MRI Images: A Comparative Analysis

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Abstract
Alzheimer's disease (AD), the most common form of dementia, affects over 55 million people worldwide. The most form of dementia progresses into three distinct stages: mild, moderate, and very mild compared to Cognitively Normal (CN). Early detection is crucial to prevent brain damage before the late stages. Convolutional Neural Networks (CNNs), a subfield of deep learning, have recently found remarkable applications in medical image processing and computer-aided diagnosis (CAD). To this end, this paper presents a new efficient multi-classification AlzCNN-Net model to enhance the accuracy and efficacy of MRI image classification for various Alzheimer's disease conditions. Initially, the training process involves utilizing open-source Alzheimer's disease datasets from the Kaggle database to classify the brain MRI into its corresponding category. To verify the model's efficacy, a comparative analysis with three pre-trained models, namely VGG16, Incep-tionV3, and MobileNetV2, has been investigated via transfer learning applied to the same dataset. As a result, the findings reveal that the AlzCNN-Net model exhibits an optimal performance, attaining the best accuracy in training with 99.67%, validation with 98.24%, and testing with 98.9% accuracy at epoch 100 with batch size 32 compared to the existing pre-trained approaches.

Keywords
Alzheimer's Disease (AD), AlzCNN-Net, Brain MRI, CNN, Deep Learning (DL), Transfer Learning.

I. Introduction

Dementia-related Alzheimer's disease is a progressive neurological disorder irreversible and degenerative condition of the brain that results in the death, discon-nection, and functionality impairment of neurons char-acterized by memory impairment and mortality in the elderly. Behaviour, cognition, memory, and reasoning are all adversely affected by genetically inherited dis-eases. It is ranked third among the elderly, following cardiovascular disease and malignancy. Alzheimer's disease (AD), which impacts 6.5 million Americans is one example of the senile disease that has emerged as a result of the ageing population. AD may affect 13.8 mil-lion individuals by 2060 if no medical advancements occur [1, 2]. AD, a condition attributed to aberrant ag-gregates and entangled fibres presently recognized as amyloid plaques and tau, was first identified by Dr. Alois Alzheimer in 1906 [3–5].
Memory is an essential component of the human condi-tion; however, individuals afflicted with Alzheimer's disease encounter a progressive deterioration in memory, culminating in amnesia and ultimately demise. Progres-sive Alzheimer's disease is distinguished by symptoms including cognitive decline, disorientation, and chal-lenges with routine tasks. In the elderly, it may result in forgetfulness, recognition difficulties with family mem-bers, or even fatality. The three primary stages of the disease are very mild, mild, and moderate. For effective treatment and to prevent brain tissue injury, precise (AD) detection and classification are vital [6].
Many images represent a healthy mind and how a healthy mind changes when afflicted with Alzheimer's disease. The physiological configuration brain form of Alzhei-mer's and

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dementia is shown in Fig.1 [7].

AD was previously only detectable posthumously, however, recent developments in neuroimaging methods such as magnetic resonance imaging (MRI) and positron emission tomography (PET) have enabled the detection of AD in living brains. In fact, Social interaction, physical activity, adherence to a Mediterranean diet, and regular sleep cycles are all preventative measures that can delay the progression of AD. The high similarity in image characteristics between healthy and diseased brains, however, complicates the diagnostic process. A resolution to this dilemma has been found in deep learning, which is capable of categorizing brain images into numerous groups, including normal and various classes of AD. By utilizing high computing plat-forms (HPCs) and graphics processing units (GPUs), the computational overhead and training of voluminous data can be completed rapidly. In general, the advancement of deep learning techniques and strategies for preventing AD is critical for the improvement of AD diagnosis and treatment [8, 9].
Deep learning (DL) provides a more user-friendly frame-work for medical image [10] classification, specifically for the early detection of Alzheimer's disease (AD) through the classification of neural images into multiple classes, and addresses each of these concerns. The monitoring of dis-ease progression by deep learning algorithms through the analysis longitudinal data can yield significant insights for researchers and clinicians. Segmenting split images is possible with the aid of deep learning techniques. Drug discovery can be aided by deep learning predictions of potential medications that target pathways associated with identifying Alzheimer's disease patients who may derive the greatest benefit from particular interventions [11, 12].

The principal contributions of this paper can be summarized as follows:

• For the precise classification of Alzheimer's disease (AD), a new fine tuning AlzCNN_Net model is designed and implemented to support computer-aided diagnosis (CAD).
• The CNN architecture is developed with extensive training and testing for various configurations on the Alzheimer's MRI Dataset acquired from the Kaggle database using epochs (50,100) and batch sizes (16,32).

• The performance of AlzCNN-Net model is methodically assessed in comparison to three widely recognized pre-trained models: VGG16, Mobile V2 Net, and Inception V3. Transfer learning methodologies are implemented to optimize these models on our dataset. Following this, a range of performance metrics were assessed to determine their efficacy.

• After exhaustive comparative analysis, the AlzCNN-Net model exhibits superior performance metrics via boosting the accuracy from 99% to 99.67% as compared to the pretrained models. It indicates that this CNN architecture accurately classifies Alzheimer's disease based on MRI data.

• Accordingly, the proposed optimal model can make a significant contribution for accurate early detection and multi-classification of Alzheimer's disease using MRI data. Specifically, this new CNN model is an effective, simple approach to assist cutting-edge medical applications in brain disorders

In this work, the proposed approach reveals the best way to classify images related to Alzheimer's disease (AD) and create an effective CNN model with a variety of training configurations, the so-called AlzCNN-Net model. The model achieves optimal performance by continuously re-fining its hyper-parameters and then comparing it to other existing models that have been investigated in this study.
The paper follows the following structure: Section II. , provides numerous prior works using Convolutional Neural network (CNN) models to classify Alzheimer's disease. Section III. presents an introductory overview of deep learning. Section IV. , presents an introduction to the architecture of the AlzCNN-Net model. The architecture and constituents of the CNN model are explicated, establishing the foundation for its implementation in the following sections. In Section V. , the methodology is elaborated upon, including the justification for model selection and the proposition of a framework. This section provides a detailed explanation of the methodology employed in the study to classify Alzheimer's disease using deep learning techniques.
Furthermore, Section VI. is devoted to the analysis and comparison of the results acquired from the conducted experiments. It entails the evaluation of diverse parameters that were employed throughout the model's training and the evaluation of the performance metrics. Finally, Section VII. draws the concluding remarks with a discourse on prospective avenues for future research.

II. RELATED WORK

Deep learning provides the methodology for classification through the extraction of complex and nuanced patterns from vast datasets. Within the domain of Alzheimer's disease (AD) research, an ever-evolving array of methodologies is striving to optimize the diagnostic procedure and forecast forthcoming medical conditions through the utilization of biomarkers. Mujahid et al. [13] suggest an ensemble model, which acquires knowledge of intricate patterns from data through the

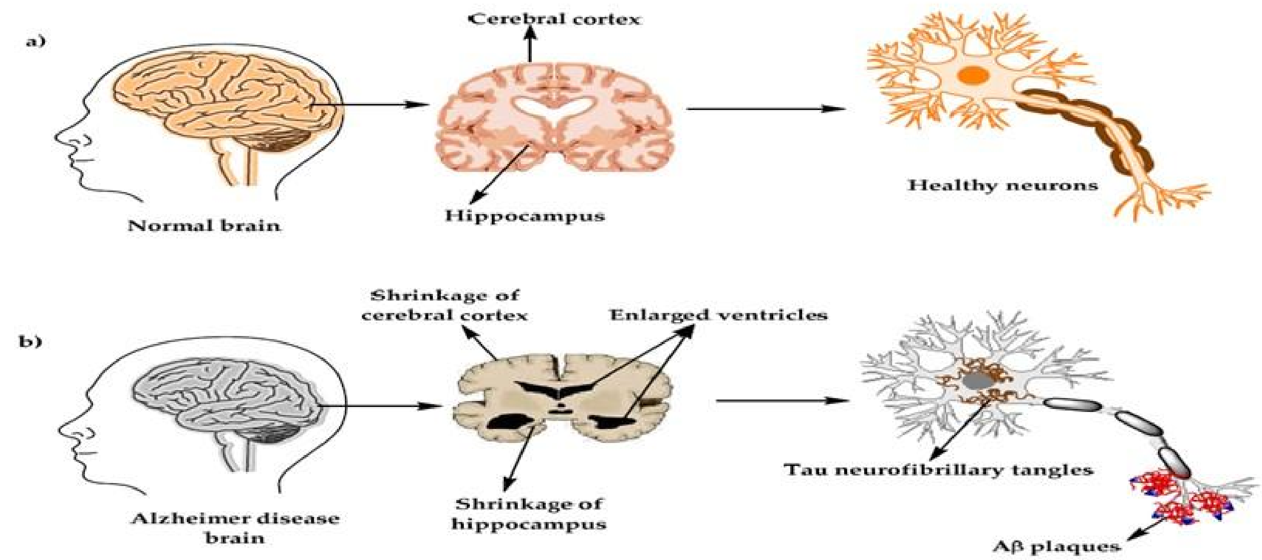


Fig. 1. The Physiological Configuration of the Brain and Neurons in (a) a Brain without AD, (b) a Brain with AD

amalgamation of predictions generated by numerous models. Utilizing the efficient net and VGG-16 architectures, the model achieves the utmost precision in disease early detection. Based on experiments performed on two publicly accessible datasets, an accuracy rate of 97.35 %t was determined. In contrary, as proposed by Altwijr et al. [14] Utilizing pre-trained convolutional neural networks were utilized, to devise a deep-learning approach that can detect Alzheimer's disease severity levels with extreme precision, especially when only sparse datasets are availa-ble. The aggregate detection accuracy of the proposed method was 99.3%, surpassing that of two established deep-learning algorithms, namely VGG16 and ResNet50. Three models developed by Çelebi et al. [15] showcases the capability of deep learning to identify Alzheimer's Disease through the utilization of tensor-based morphometry; their respective accuracy rates were 93% and 92%. Hussain et al. [16] propose a method for categorizing distinct phases of dementia from MRI images using watershed segmentation in conjunction with RF, SVM, and CNN algorithms. SVM obtains a 96.25% accuracy, outperforming all other classification techniques.

Mahmud et al. [17] use methods for extracting relevant features from MRI data, training pretrained models, and ensemble classifiers. The approach achieves an accuracy of 95% for combined ensemble models. For greater feature diversity, Hanoon et al. [18] propose a modified 50-layer residual neural network (ResNet) with addi-tional convolution layers and a leaky ReLU. The classification of AD stages was accomplished by the method with 97.49% accuracy, 98% precision, 98% recall, and 98% f1-score. In Arafa et al. [19], a CNN architecture and a pre-trained VGG16 model were both implemented. The proposed procedure is efficacious in the diagnosis of Alzheimer's disease. The model demonstrates exceptional performance, achieving an accuracy rate of 97.44%. By uti-lizing deep neural networks, Bamber et al. [20] sought to diagnose and monitor Alzheimer's disease. With an overall accuracy of approximately 98%, a convolutional neural network featuring a shallow convolutional layer outperforms the majority of prevalent techniques. AbdulAzeem et al. [21] utilize cross-validation to train the CNN. The CNN model consists of three convolutional layers and max-pooling. Various algorithms, such as the Glorot uniform weight initializer and Adam optimizer are used. Experiments show the proposed framework out-performs the state-of-the-art techniques for both binary and multi-classification. An entirely automated approach for the diagnosis and classification of brain tumors is put forth by Emrah Irmak [22], employing convolutional neural networks (CNN). The first of three proposed models for various classification tasks achieves an accuracy of 99.33% in detecting brain tumors. The accuracy of the second model in classifying tumors into five types is 92.66%, while the accuracy of the third model in classifying tumors into three grades is 98.14%. A comparison is made between the proposed CNN models and alternative models. An apparent rationale for the proposed CNN models' superiority over pre-trained networks is that the latter are pretrained deep learning models that were originally developed and trained on standardized datasets to address general image classification challenges. In contrast, the CNN models that have been suggested are intended for more specialized tasks, including the detection of brain tumors and the classification of tumor types and grades. An additional plausible explanation for the superior performance of the proposed CNN models compared to the pre-trained models is that the proposed CNN architectures have been hyper-parameter-optimized to yield the most favorable out-comes for the particular problems at hand.

On the other hand, Khan [23] combines data augmentation and image processing with the convolutional neural network (CNN) to classify brain MRI scan images as cancerous or non-cancerous. The CNN model outperforms pre-trained models such as VGG-16, ResNet-50, and Inception-v3 with a 100 percent accuracy rate on a small dataset. In comparison to pre-trained models, the model exhibits superior accuracy and demands less computational capacity. The reason for developing an original neural network algorithm as opposed to utiliz-ing widely recognized ones such as VGG16, Inception v3, and ResNet is these algorithms trained on ImageNet and other large data sets, which necessitated intensive processing capacity for fine-tuning via freezing layers and transfer learning. Noteworthy, one of the obstacles that prompted the creation of the neural network algo-rithm CNN from scratch is that the images used in these algorithms are of a fixed size for each algorithm, which requires changing the size of the images to The size used in these algorithms. In contrary, since traditional CNN architectures often contain a large number of parameters, these algorithms were trained on a large amount of data sets such as ImageNet, and to use them, they re-quire fine-tuning by freezing layers to reduce parameters and replace fully connected layers using transfer learning which can be computationally expensive to train and deploy. However, CNN architectures also pro-vide better interpretability and explainability, allowing researchers to gain insights into the model's decision-making process. The model also considers image size, as traditional CNN architectures, may not be optimal for medical imaging data. This flexibility reduces the need for preprocessing steps, simplifies workflows, and potentially improves computational efficiency.

In this work, the AlzCNN-Net deep learning model was created to tackle medical imaging tasks like Alzheimer's disease classification.

As known, the basic CNN algorithms are designed for general computer vision tasks; but they may not be an optimal solution for specific applications like Alz-heimer diagnose. Therefore, this paper introduces a new and effective fine-tuning AlzCNN_Net model to achieve optimal performance by exploring the hyper-parameters like choosing a number of layers, activation functions, dropout rates, and optimization algorithms. For further recent studies, Table I provides a concise summary of several additional models that are relevant to classify and diagnose the early and various impairment condi-tions of dementia and Alzheimer's diseases [24–37]. For instance, in [24], a 3D Dense Net was trained for 600 MRI images, but with an accuracy of up to 83.33%. In [29], Alzheimer's Net achieves 98.67%; meanwhile, in [32], the accuracy is boosted to 99.43%, 99.75%, and 99.13% using two CNNs and the combination of them, respectively. In [33], the accuracy of 100% using CNN-GCN model for 6400 datasets.; and in [36], two CNNs-LSTM- and VGG16-SVM models with data augmenta-tion achieves 99.92% and 98.67% for 6400 MRI images, respectively.

III. Deep Learning (DL)

DL is an area of machine learning that specializes in the construction of enormous neural network models to en-able accurate data-driven decisions [38, 39]. The rapid growth of deep learning, an approach pioneered by Dechter in 1986 [3], is due to the proliferation of enormous data sets and developments in parallel computing hardware. Its capacity to learn and its multiple layers of architecture enables it to solve complex problems. DL is utilized by the healthcare industry, consumer technologies, online businesses, and autonomous vehicles to analyze medical imaging scans.

DL comprises Convolutional neural networks (CNNs) that have experienced a surge in importance across various domains, including but not limited to image pro-cessing and analysis, computer vision tasks, and medical imaging applications. DL has demonstrated promising results in Alzheimer's disease research and diagnosis by analyzing cognitive assessments, genetics, and lifestyle to determine the risk of developing the disease and by detecting subtle brain changes associated with the con-dition [40].

IV. Convolution Neural Network (CNN)

Convolutional neural networks are models that are employed to analyze data that possesses multiple dimensions, such as time series and images. CNNs are well-known deep learning algorithms, and deep neural networks are extensively implemented in the domains of image segmentation and classification using basic data characteristics as input, and they organize them into intricate patterns to produce feature maps. CNNs, which were initially proposed in 1989, garnered considerable interest after their remarkable performance in the 2012 ImageNet Competition. The error rate can be halved by applying CNN to a dataset containing one thousand classes and millions of images.

Composed of convolution, pooling, activation function, and entirely connected layers, the CNN architecture is intricate. Activation functions like the rectified linear unit (ReLU) and leaky ReLU change data in nonlinear ways, while pooling

TABLE I.
RECENT STUDIES ON ALZHEIMER'S DISEASE DIAGNOSE

Ref	Year	Method	Image Type	Data Set	Accuracy
[24]	2020	3D Dense Net	MRI	600	83.33%
[25]	2021	Deep Transfer ENSEMBLE	MRI	813	99.05% 85.27%
[26]	2023	HEMRDTL model: hybrid EEG and RPCA incorporated deep transfer learning	CT MRI	416	99%
[27]	2023	An SVM classifier-based model constructed with graph kernels.	MRI	474	92%
[28]	2023	ResNet-152, Alex Net	MRI	N/A	99.96% 98.56%
[29]	2023	Alzheimer-Net	MRI	2456	98.67%
[30]	2023	Mobile Net	MRI	1101	96.6%
[31]	2023	ResNet	MRI	150	91%
[32]	2024	Two CNN Models and combining outputs	MRI	1296 T1 weighted MRI scan	99.43% 99.75% 99.13%
[33]	2024	CNN-GCN	MRI	6400	100%
[34]	2024	Ensemble1 VGG16, VGG19 Ensemble2 Dense Net169, Dense Net201)	MRI	6400	92% 95%
[35]	2024	Machine learning	MRI	---	76% 89%
[36]	2024	CNNs-LSTM-with Aug VGG16-SVM-with Aug	MRI	6400	99.92% 98.67%
[37]	2024	Soft-NMS into Faster R–CNN+ Bi-GUN	MRI	406	98.97
This work	2024	Three AlzCNN-Net Models	MRI	6400	99.4% 99.5% 99.7%

downsamples the results of convolutional layers that make feature maps. In the final CNN layer, input data is predicted, and network parameters are determined through the reduction of the loss function separating the predictions and ground truth labels, with regularization constraints also taken into account [41]. The network's weights are modified during each iteration by employing Adaptive Moment Estimation and back-propagation techniques until convergence is achieved the input layer is convolutionally processed using trainable kernels to generate these feature maps. Nonlinear trans-formations and aggregation contribute to the convergence of the network. Based on the feature maps that have been processed, predictions are produced via completely connected layers. In time-series analysis, an architecture with one dimension is implemented [42, 43].

V. METHODOLOGY

A. *Propose Framework*

The proposed methodology comprises the subsequent stages, including the data acquisition, preprocessing, model selection, and evaluation metrics. Fig. 2 demonstrates the general framework of the proposed AlzCNN-Net Model.

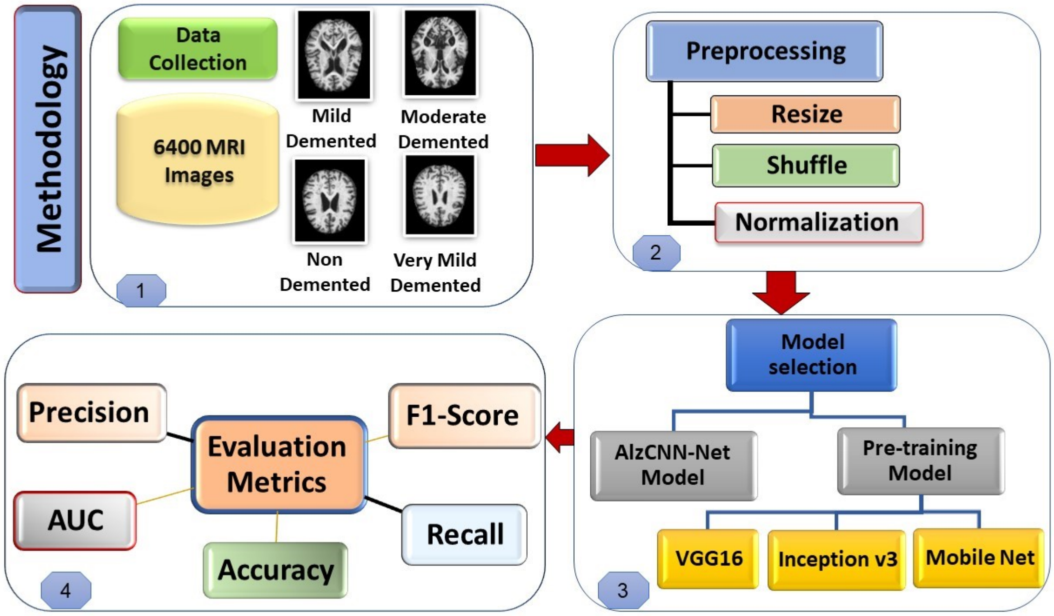


Fig. 2. The Proposed Methodology

1) *Acquisition of data*

The approach employs a dataset comprising an Alzhei-mer's MRI Dataset, with each image having a resolution of 128 x 128 pixels. The images formats are JPEG. In all, 6400 MRI images acquired through the publicly available Kaggle plat-form comprise the dataset [44] dataset classi-fication into four categories: Class "1" comprises 896 images of mild dementia, Class "2" comprises 64 images of moderate dementia, Class "3" comprises 3200 images of non-dementia, and Class "4" comprises 2240 images of very mild dementia. The dataset depicted in Fig. 3 was utilized as the input data for every model.

2) *Preprocessing*

The training process of the AlzCNN-Net neural network is optimized by reducing to optimize the neural network's train-ing procedure, the dimensions of the images are reduced to (100,100), resulting in an exact pixel count for each image. To reduce the intricacy of the model and prevent increased computational demands and training time caused by a higher pixel count in an image.

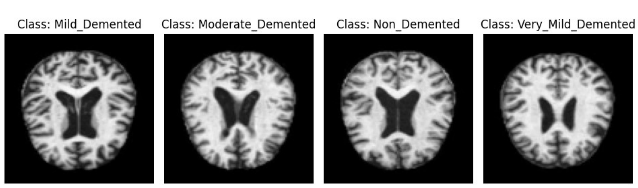


Fig. 3. The four classes of the Alzheimer dataset

In deep learning and data analysis, shuffling is a prevalent technique employed to guarantee that the data is presented to a model in an arbitrary sequence. This prevents any pos-sible biases or patterns that may have been present in the initial order from having an impact on the training process. The process of shuffling enhances the generalizability of a model by reducing its reliance on the sequential arrangement of training data samples. The selection of the normalization technique is contingent upon the data's properties and the machine learning model's specifications. Strictly choosing the proper methodology is critical to prevent the introduction of bias or the distortion of data. By rescaling attributes with a mean value of zero and a standard deviation of one, data normalization eliminates redundancies and simplifies the de-tection of subtle differences.

3) *Data Set Split*

An initial partitioning of the dataset results in the crea-tion of two discrete sets: the training set, comprising 80% of the total data, and the testing set, comprising the remaining 20%. Additional subsets are created from the training set: a training set comprising 90% and a valida-tion set comprising 10% of the original training data. A training set is utilized to train the AlzCNN-Net model. The validation set, on the other hand, is utilized to assess the performance of the model at regular intervals during training, thereby assisting in the reduction of overfitting risk. Finally, the efficacy of the model's general-

TABLE II.
THE DATASET'S PARTITIONING INTO TRAINING, TESTING, AND VALIDATION SETS

Total data set	Training set	Testing set	Validation set
6400	4608	1280	512

ization to data that it has not encountered is evaluated using the testing set. The dataset is partitioned into training, testing, and validation sets, as shown in Table II.

B. Model Selection

The AlzCNN-Net model is designed, implemented, and tested with pre-training CNN models to verify its perfor-mance on unexplored data. The study uses Python version 3.10.12, the Kaggle platform, a GPU with 3.7 compute cores, 2496 CUDA cores, 12 GB of GDDR5 VRAM, and the NVIDIA P100 platform. Numerical computations were performed using Scikit-learn, TensorFlow, OpenCV, and NumPy. The model was additionally constructed and assessed in the Google Colab environment. Deep learning tasks were executed using Python version 3.10.12, TensorFlow, and Keras. Computational tasks were efficiently managed with the assistance of a 15 GB T4 GPU. These tools enable the comprehensive evaluation of the model's performance on both familiar and unfamiliar data.

1) The Proposed AlzCNN-Net

The foundational model selected for this study is a sequential convolutional neural network (CNN), which has been customized to fulfil the classification objectives related to Alzheimer's disease. The broad applicability, ease of use, and flexibility in achieving the desired model support the choice to use a sequential CNN for image classification tasks. The model that has been put forth to analyze image data is organized in the form of 'Conv2D' layers, which are three convolutional layers that are stacked in succession. To optimize feature capture and spatial dimension reduction, a 'MaxPooling2D' layer was incorporated after every convolutional layer, utilizing a 2x2 pooling window. The first convolutional layer processes the input shape (100, 100, 1), a 3x3 kernel, and ReLU activation, which is a representation of grayscale images in the input and filter (32). 64 filters, a 3x3 kernel, and ReLU activation are implemented in the second convolutional layer. Furthermore, Dropout was implemented in this layer to prevent overfitting. ReLU activation, 128 filters, and a 3x3 kernel are all components of the third convolutional layer. Similar to the second layer, dropout is incorporated to mitigate the risk of overfitting.

In preparation for the fully connected layers that follow the convolutional layers, the output is converted to a one-dimensional vector using the 'Flatten ()' function. Fully connected, dense layers are implemented for the classification

TABLE III.
ALZCNN-NET MODEL SUMMARY

Layer (type)	Output Shape	Parameter
conv2d_15 (Conv2D)	(None, 98,98,32)	896
max_pooling2d_15 (MaxPooling2D)	(None, 49,49,32)	0
conv2d_16 (Conv2D)	(None, 47,47,64)	18496
max_pooling2d_16 (MaxPooling2D)	(None, 23,23,64)	0
dropout_10 (Dropout)	(None, 23,23,64)	0
conv2d_17 (Conv2D)	(None, 21,21,128)	73856
max_pooling2d_17 (MaxPooling2D)	(None, 10,10,128)	0
dropout_11 (Dropout)	(None, 10, 10,128)	0
flatten_5 (Flatten)	(None, 12800)	0
dense (Dense)	(None, 128)	1,638,528
dense_1 (Dense)	(None,4)	516
Total params: 1732292 (6.61 MB)		
Trainable params: 1732292 (6.61 MB)		
Non-trainable params: 0 (0.00 B)		

assignment. The first dense layer has 128 units and uses the ReLU activation function to classify things into multiple groups. The last dense layer has four units and uses the SoftMax activation function to show the output groups. Thus, the AlzCNN_Net model is illustrated in Fig. 4, and resulting model summary is presented in Table III.

2) Pre-training Models

This research undertakes a comparative evaluation of three pre-trained models, MobileV2 Net, VGG16, and InceptionV3 Net, which were all trained to utilize the ImageNet dataset and were applied to the Alzheimer MRI Dataset. The strategy is implemented by excluding inex-tricably linked layers and integrating custom classifica-tion layers [45].

The inclusion of a GlobalAveragePooling2D layer reduces the spatial dimensions of the data after convolutional layers through the computation of the mean of each value found in each feature map. In the final classification layer, a Dense layer with four units and a SoftMax activation function is implemented. This particular stratum has been purposefully engineered to facilitate a classification task comprising four discrete classes. The training procedure preserves the initial weights of the VGG16, Inception V3 Net, and MobileV2 Net layers while updating the weights of the additional layers (GlobalAveragePooling2D and Dense). However, the base model's layers remain frozen throughout the process. By ad-

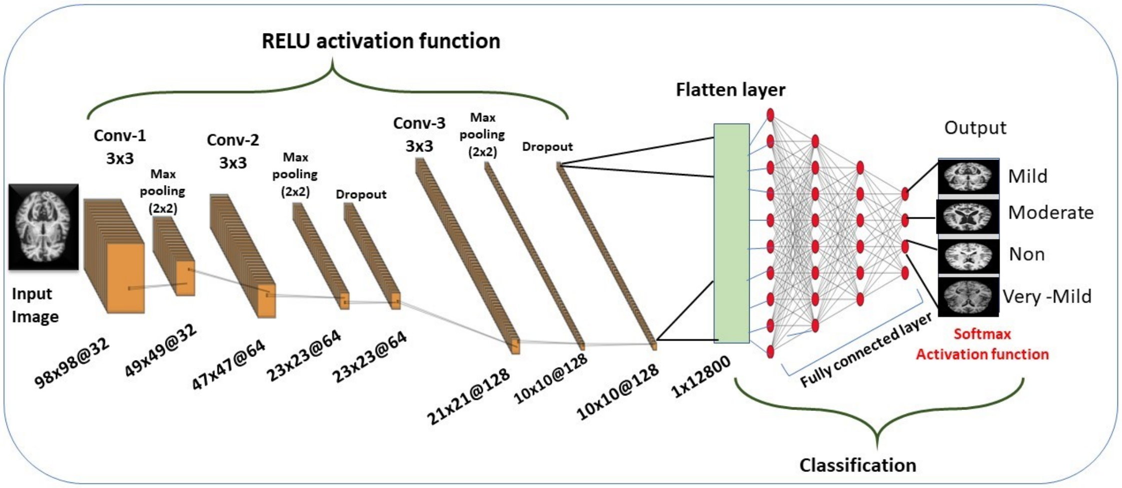


Fig. 4. AlzCNN_Net Architecture

hering to this procedure, the advantages acquired from the previously trained models on the ImageNet dataset are maintained and tailored to fulfil the specific classification goal [46].

C. Performance Metrics

Metrics are frequently employed in binary and multiclass classification tasks to evaluate the performance of ma-chine learning models in domains such as natural lan-guage processing, finance, and healthcare [47]. The confusion matrix serves as a visual representation of the performance of a classification model in two dimensions. True positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) are its constituent values. It is essential for determining and quantifying advancements in deep learning methodologies, comparing current approaches, and evaluating the scale, quality, and repercussions of data augmentation.
Although its initial purpose was binary-class classification, the confusion matrix can be expanded to encompass multiple classes [48].

• F1-Score: The F1-Score is a metric that merges recall (sensitivity) and precision, two crucial performance indicators, into a solitary value [47]. Eq. 1 represents this F1-Score as,

$$F1-score = \frac{2\times TP}{2\times TP(FP+FN)} \tag{1}$$

• Precision, also known as positive predictive value, quantifies the proportion of accurate positive predictions. Put differently, it measures the proportion of accurate positive predictions generated by the model. Accuracy values, such as 80%, are generally considered acceptable. [47]. The Eq. 2 defines precision.

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

• Recall (Sensitivity): It evaluates the model's capacity to precisely classify positive cases from the total number of positive cases. The algorithm determines the ratio of accurately predicted positive cases to the overall count of confirmed positive cases [47]. The typical range of acceptable recall values is 70–90%. The expression for sensitivity is given by Eq. 3.

$$Precision = \frac{TP}{TP+FN} \tag{3}$$

• Accuracy: The evaluation of accuracy is of the utmost importance when it comes to comparing and establishing standards for deep learning methods, assessing the impact of augmentation, and evaluating the quantity and quality of data. Good values are generally defined as exceeding 80%, while outstanding values are those surpassing 90%. The Eq. 4 is employed to determine the accuracy of the model [48].

$$Accuracy = \frac{TP+FN}{TP+TN+FP+FN} \tag{4}$$

• Area Under Curve (AUC): is a metric used for classification models. It represents the region under the ROC curve. The value of the parameter spans from 0 to 1, where a lesser value signifies inferior performance and a higher value is superior performance.

TABLE IV.
THE HYPER - PARAMETERS OF ALZCNN-NET

Hyper-parameter	Value
Activation function	ReLU, Leaky ReLU
Learning Rate	0.0001
Optimizer Adam	Adam
Loss	Categorical Cross Entropy
Batch size	16, 32
Dropout rate	0.25
Epochs	50 , 100
Output activation function	Soft Max

VI. RESULTS AND ASSESSMENT OF PARAMETERS

This section presents the outcomes of training CNN model (AlzCNN-Net) using a dataset comprising medical images that are pertinent to the diagnosis of Alzheimer's disease. The efficacy of pre-trained CNN models through the implementation of transfer learning was investigated as a prevalent methodology in the field of deep learning. In conclusion, a performance comparison was made be-tween AlzCNN-Net and pre-trained models as well as the most recent deep learning approaches for Alzheimer's disease diagnosis.

A. Training Process

The training phase comprises 4608 data points, while the testing phase includes 1280. Inception V3, AlzCNN_Net, VGG16Net, and Mobile Net were the four networks that were chosen. A data allocation of 80% was designated for training purposes, while the remaining 20% was set aside for testing. Throughout the training phase, changes in loss functions, accuracy rates, and validation accuracy rates were evaluated independently for each model. The adaptive learning rate optimization technique Adam (Adaptive Moment Estimation), which combines AdaGrad and RMSProp, is used in the training phase of the AlzCNN-Net model. Compared to more conventional techniques like stochastic gradient descent, this one al-lows for faster convergence and maybe greater performance at learning rate (0.0001). Because of Adam's adaptive nature, training is more stable and robust [49]. In Table IV, the hyper-parameter values employed during the training of the AlzCNN-Net model are detailed.

1) Results of AlzCNN-Net Model

The effectiveness of the AlzCNN_Net model was evaluated in this study by manipulating the number of training periods and sample sizes. A higher level of accuracy was observed when the training period was extended to 100 epochs as opposed to 50 epochs. Prolonged training periods improve the ability to recognize more intricate patterns in the data. Empirical evidence indicates that when the batch size is reduced to 16, convergence can be accelerated; nevertheless, processing assumptions become more susceptible to scrutiny; on the other hand, generalization is improved with a batch size of 32. As a result, Table V presents an illustration of the efficacy of CNN models utilizing various sample sizes and epochs.

Fig. 5, shows the trends in accuracy of the AlzCNN-Net model during the training and validation stages. While bigger batch sizes, such as 32, reduce parameters, smaller batch sizes, such as 16, yield greater performance in higher parameter adjustments. By using fewer parameter updates per epoch, the research indicates that a higher batch size may aid in a smoother convergence process. In contrast, a smaller batch size speeds up convergence but leaves processing assumptions open to criticism. In-creased recognition of complex patterns in data can be achieved with longer training times.

On the other hand, more group size may have an impact on the loss trajectory, as seen by the loss contours of the model throughout 50 training epochs shown in Fig. 6. Model convergence and loss trajectory are also highly dependent on sample size and number of epochs. For 100 epochs and batch size 32, the accuracy is increased from 99% to 99.6% with 0.01 loss in training mode and 98.9% with 0.03 loss in testing mode, according to the performance evaluation of the suggested CNN models across various sample sizes and epochs during training, validation, and testing modes.

On the other hand, the confusion matrix in this study, which uses epochs 50 and 100 with batch sizes of 16 and 32, dis-plays all instances analyzed using the fundamental CNN model in Fig. 7. The model's capability to accurately classify positive cases across various categories is illustrated in Fig. 7a. In particular, the true positives included (166) mild dementia, (15) moderate dementia, (614) non-dementia, and (442) very mild dementia. In contrast, the model predicted (155) mild dementia, (14) moderate dementia, (613) Non-dementia, and (448) very mild dementia as true positives in Fig. 7b. As for Fig. 7c, the model predicted the following: (168) mild dementia, (17) moderate dementia, (611) Non-dementia, and (464) very mild dementia as true positives. While the model achieved the positive result prediction: (184) mild dementia, (15) moderate dementia, (627) Non-dementia, and (449) very mild dementia as true positives in Fig. 7d. Based on the number of epochs employed and the batch sizes in each case, it has been ob-served that the predictions in the four categories vary in the four examples. As a result, we can say that, in the two categories of moderate dementia and very mild dementia, the forecast in Fig. 7d performed the best, while the remaining instances had predictions that were similar to Fig. 7d. This suggests that prediction accuracy is affected by both the number of epochs and the magnitude of payments.

TABLE V.
PERFORMANCE OF ALZCNN-NET MODEL ACROSS DIFFERENT BATCH SIZES AND EPOCHS

Training Mode						Testing Mode	
Epoch	Batch size	AC %	Val_AC %	Loss	Val_ loss	AC %	Loss
50	16	99.4	98.2	0.01	0.06	96.6	0.1
	32	97.2	95.7	0.08	0.1	96	0.1
100	16	99.7	99.2	0.05	0.01	98.4	0.04
	32	99.67	98.2	0.01	0.04	98.9	0.03

TABLE VI.
HYPER-PARAMETERS OF PRE-TRAINING CNN MODELS

Hyper- parameter	Value
Activation function	ReLU
Learning Rate	0.0001
Optimizer Adam	Adam
Loss	Categorical Cross Entropy
Batch size	32
Epochs	100
Output activation function	Soft Max

TABLE VII.
PERFORMANCE EVALUATION OF PRE-TRAINING CNN MODELS

Training Mode					Testing Mode	
Model	AC%	Val_ AC %	Loss	Val_ loss	AC %	Loss
VGG 16	56.81	55	0.8	0.9	56	0.9
Mobile Net	72.11	63	0.6	0.7	67	0.7
Inception V3	75.56	64	0.5	0.7	67	0.7

2) *Results of Pre-training Models*

In this paper, the transfer learning strategy was used to train the pre-trained models VGG-16, Mobile Net, and Inception-v3 using the same dataset. This action was taken to facilitate a direct comparison with the efficacy of our CNN model. The obtained results validate the precision of every pre-trained model throughout the training and validation. Table VI lists the hyper-parameter values that were employed during the training phase of the Pre-training CNN model. The findings derived from these investigations are briefly presented in Table VII.

TABLE VIII.
THE RESULTS OF PERFORMANCE METRICS

Model	AC %	Precision %	Recall %	F1-Score %	AUC %
AlzCNN	99.67	99.6	99.6	99.2	99.99
VGG16	56.81	69.62	38.45	32.91	84.98
Mobile Net	72.11	78.70	90.94	65.42	92.54
Inception V3	75.56	80.68	67.14	76.16	93.99

B. *Performance Evaluation Vs. Pre-trained Transfer Learning*

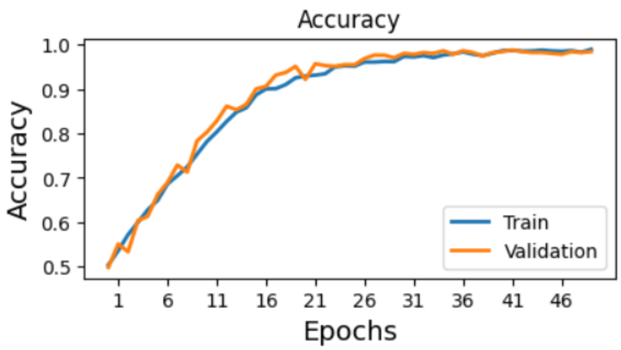
To verify the effectiveness of the proposed AlzCNN-Net model, a comparative analysis with three well-established deep learning models, VGG16, Mobile Net, and Inception V3 Net, are considered utilizing batch size 32 and epoch 100. Precision, probability, recall, and F1 score were assessed as performance metrics for the trained model. The results of these measurements are shown in TableVIII. The findings indicate that the AlzCNN-Net model exhibits superior performance in terms of loss magnitude and accuracy when compared to the alternative transfer learning models that were employed.

C. *Evaluation for Different Configurations of Parameters*

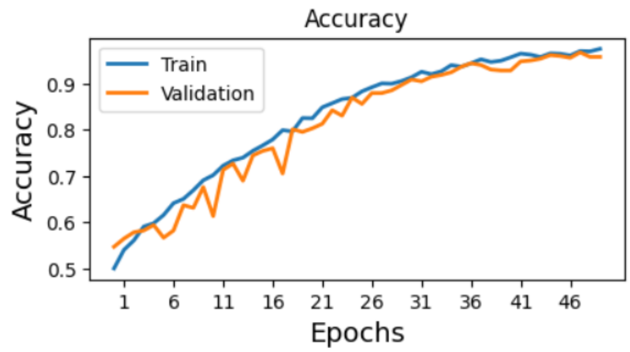
The influence of parameters on accuracy was investigated through a series of experiments conducted in AlzCNN_Net. The accuracy results obtained from evaluating different batch sizes (16, 34, 512) over time intervals of 30, 50, and 100 epochs were plotted in Fig. 8. The results showcase the effect of hyper-parameters ef-fect on the accuracy. As noticed, Batch size 34 with Epoch 30 outperforms the other CNN models with an accuracy of 99.9% for training and 94.7% for testing. Noteworthy, the increase in batch size may not always improve the generalization of the designed CNN.

D. *Comparison with Existing Models*

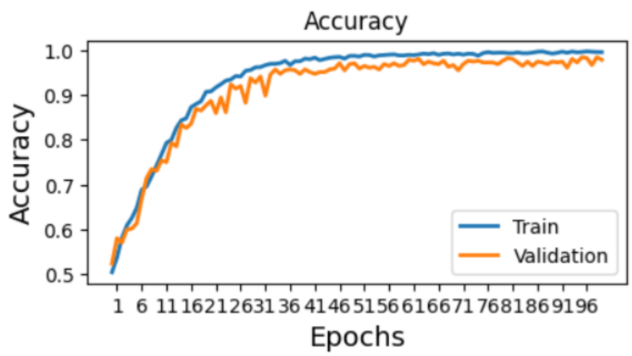
Parallel analyses were performed on a variety of scenarios in order to compare the AlzCNN model to other comparable



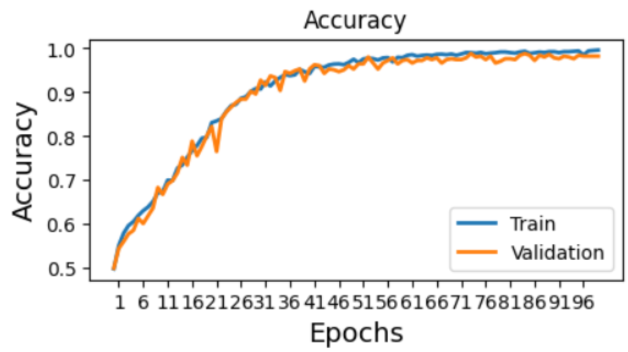
(a)



(b)



(c)



(d)

Fig. 5. The Accuracy of Training and Validation: a) Epoch 50 Batch size 16. b) Epoch 50 Batch size 32. c) Epoch 100 Batch size 16. d) Epoch 100 Batch size 32

works. Fig. 9 firstly summarizes a comparison performance between the AlzCNN model and the DEMNET architecture is considered by Murugan et al. in [50]. The DEMNET structure comprises four DEMNET blocks, each consisting of two convolutional layers, batch normalization, and a max-pooling layer for multiclass classification using the ReLU activation function. In this context, in [51], a deep learning-based ensemble method is another approach to introducing the six best individual CNN-based classifiers with ac-curacies of 98.57%, 96.37%, 94.22%, 99.83%, 93.88%, and 93.92% for early Alzheimer disease diagnose.

Next, a AlzCNN-Net is compared in the second sce-nario with a modified residual neural network RestNet that incorporated the Leaky ReLU activation function with multiclass proposed by Hanoon et al. [18]. Finally, another model proposed by AbdulAzeem et al. [21] is considered in the third scenario. The CNN architecture of this model consists of three convolutional layers, with a max-pooling layer. The model incorporates a binary class with a ReLU activation function. The ac-curacy of the AlzCNN-Net model is assessed in comparison to the aforementioned comparable works. As a result, it was found that the results reveal the superior-ity of the AlzCNN-Net models for both binary classification and multiple classification compared to the existing studies as shown in Fig. 9 and the summary of the models' comparison is presented in Table IX. In a related study [52], a CNN algorithm was devel-oped for classifying Alzheimer's disease, utilizing SMOTE and K-fold cross-validation techniques. The CNN attained a training accuracy of 98.1%, while AlzCNN-Net-4 achieved a training accuracy of 99.67%. Additionally, the transfer learning methods explored in this study showed higher effectiveness in classifying brain tumors compared to their applica-tion in Alzheimer's disease, as reported in [53]].

VII. Conclusion

To classify and identify medical images that contain Alzheimer's disease, this research paper introduces a deep-learning framework that employs Convolutional Neural Network (CNN) architectures. To assess the effectiveness of the model at different stages of the training phase, the research employs a variety of performance metrics. The AlzCNN-Net model

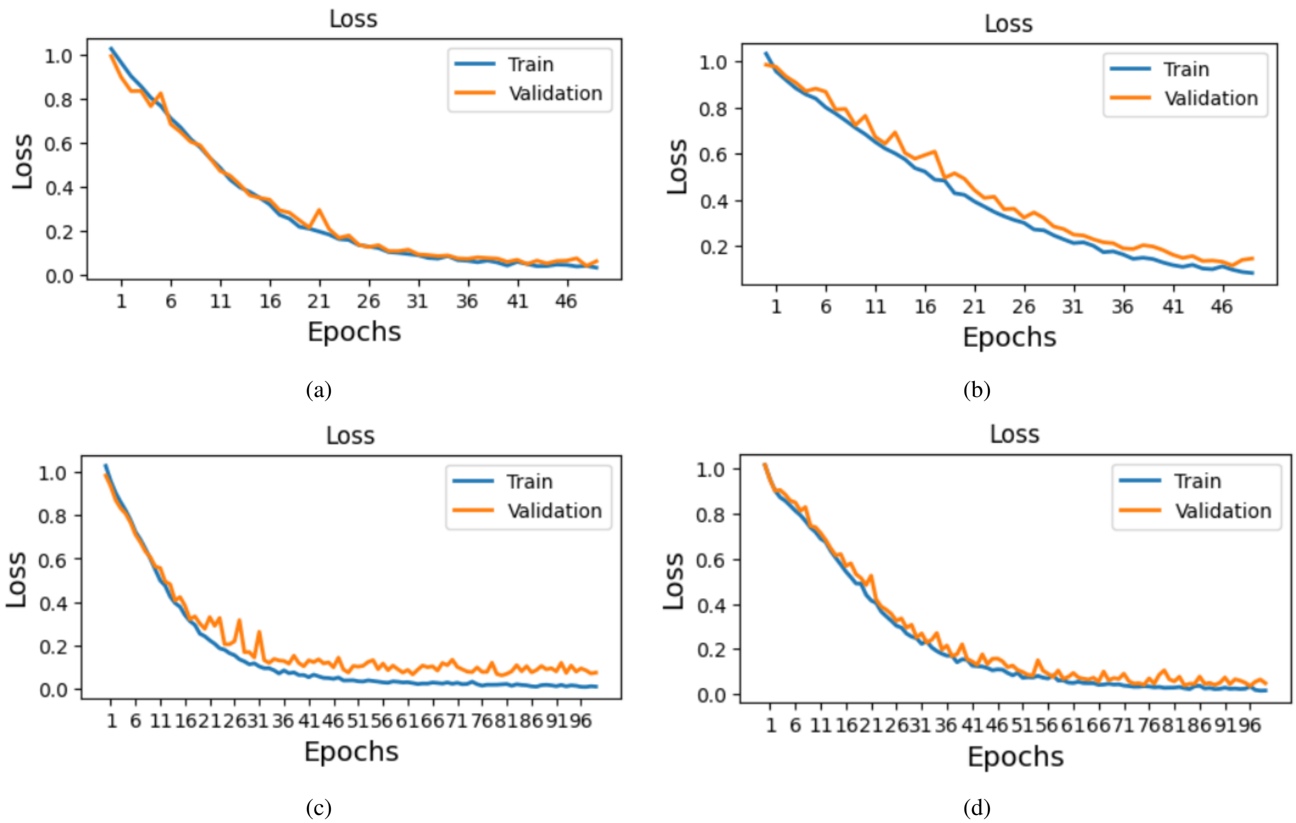


Fig. 6. The Loss of Training and Validation: a) Epoch 50 Batch size 16. b) Epoch 50 Batch size 32. c) Epoch 100 Batch size 16. d) Epoch 100 Batch size 32

undergoes fine-tuning.

Using a range of hyper-parameters and layers to sort Alzheimer's disease into its subtypes: very mild dementia, moderate dementia, non-dementia, and mild dementia. The study looks into four different training configurations: one with 50 epochs with a batch size of 16 then 32, and the second with 100 epochs and a batch size of 16 then 32. The results obtained from the latter configuration were prefer-able, and no overfitting issues were encountered. The dataset used in this study was made up of MRI images of people with Alzheimer's. It was tested against three differ-ent pre-trained models: VGG16, Mobile NT v2, and Inception V3. When training for 100 epochs with a group size of 32, the most favorable results were obtained. With the Adam optimizer and a learning rate of 0.0001, AlzCNN-Net demonstrated its optimal performance, attaining remarkable accuracy in training at 99.67%, validation at 98.24%, and testing at 98.9%. For future work, this model can be developed to classify and detect a wide range of medical conditions, such as adrenal tumors, brain tumors, and breast tumors, through the modification of hyper-parameters. In particular, the study may investigate the damages related to AD and its stages can be distinguished in sagittal and horizontal MRI using transfer learning (TL) tools.

TABLE IX.
MODELS COMPARISION SUMMARY

Models	Batch size	Epoch	Train AC%	Test AC%
AlzCNN-Net-1 (Multiclass)	16	50	99.4	96.6
Ref. [50] (Multiclass)	16	50	96	85
AlzCNN-Net-2 (Multiclass)	32	100	99.5	98
Ref. [18] (Multiclass)	N/A	N/A	99	97
AlzCNN-Net-3 (Binary class)	32	50	99.7	99.3
Ref. [21] (Binary class)	N/A	N/A	99.95	N/A

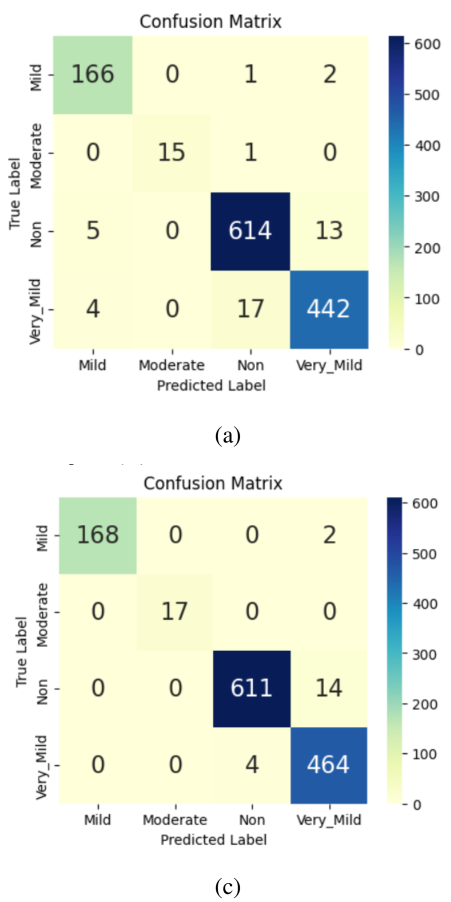


Fig. 7. The Confusion Matrix of the four AlzCNN-Net model Configurations. a) 50 Epochs Batch size 16. b) 50 Epochs Batch size 32. c) 100 Epochs Batch size of 16. d) 100 Epochs Batch size 32

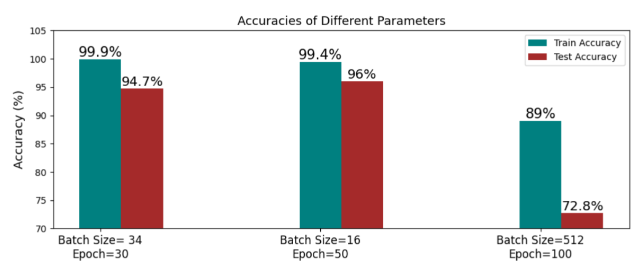


Fig. 8. The effect of different hyper-parameters on the accuracy metric

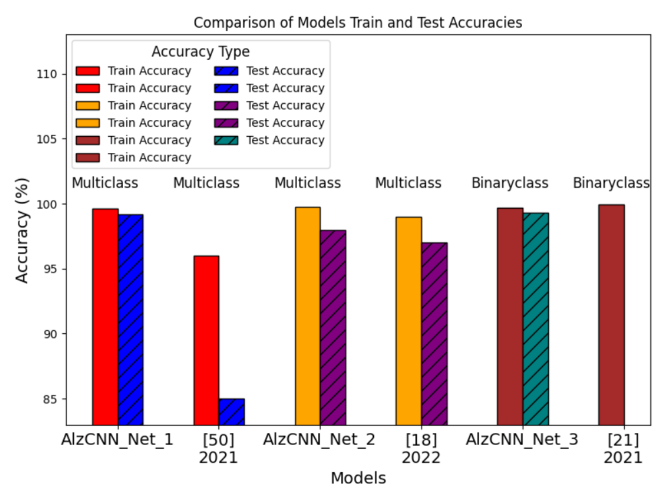


Fig. 9. A Comparative Analysis for Binary and Multiclass CNN Models with Different RelU Functions

Conflict of Interest

The authors have no conflict of relevant interest to this article.

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