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Performance evaluation of various optimizers on Alzheimer’s disease classification using deep neural network

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Abstract

The proposed work focuses on using transfer learning and CNN models for the classification of Alzheimer's Disease (AD) based on different classes of datasets. The goal is to improve the early diagnosis and classification of AD, which can contribute to better patient recovery and management. The study compares the performance of four different CNN models: AlexNet, GoogLeNet, SqueezeNet, and MobileNet V2. These models have been widely used in various computer vision tasks and have proven to be effective in image analysis. Additionally, three different optimizers are evaluated: Stochastic Gradient Descent with Momentum (SGDM), RMSProp, and ADAM. Optimizers play a crucial role in training deep neural networks, as they determine how the model updates its weights during the learning process. According to the results of the study, the MobileNet V2 model with the SGDM optimizer achieved the highest classification accuracy of 91% among all the tested classifiers. Here, datasets are taken from Kaggle and Mobilenet classifies the output into four classes namely Very Mild Demented, Mild Demented, Moderately Demented, Non-Demented. This suggests that this combination is particularly effective for AD diagnosis and classification based on the given datasets. The automated Alzheimer's disease classification system developed in this work has the potential to identify early signs and symptoms of the disease. Early detection is crucial because it allows medical professionals to intervene at an earlier stage, providing timely treatment and management strategies. By leveraging medical image analysis and transfer learning techniques, this system can contribute to more effective and efficient AD diagnosis, leading to improved patient outcomes.

*Keywords: Alexnet, Googlenet, Squeezenet, Mobilenetv2, ADAM,RMSProp and SGDM, AD Cla*ssification

1. Introduction

Alzheimer's Disease (AD) is a neurodegenerative brain disorder that affects a significant number of people worldwide. As you mentioned, approximately 50 million individuals are affected by AD globally (Raza etc. 2023), with over six million in the United States alone. Additionally, there are currently 9.44 lakh (944,000) individuals living with dementia (Arafa etc.2023).AD primarily affects older individuals, typically those aged 65 and above. The disease is characterized by progressive memory loss and the deterioration of thinking and learning abilities.

It also leads to a reduction in the size of the hippocampus and cerebral cortex, which are important brain regions involved in memory and cognitive processes. The shrinkage of these areas contributes to the irreversible damage caused by AD and can ultimately result in death. Although there is currently no complete recovery from AD, early diagnosis and treatment can significantly improve the health condition of patients. The stages of AD classification are based on the patient's brain and health condition and can be categorized as Mild Cognitive Impairment, Mild Alzheimer's, Moderate Alzheimer's, and Severe Impairment.

“Rallabandi etc. (2020)” proposed a machine learning classifier based on the Radian Basis Function (RBF) kernel and non-linear Support Vector Machine (SVM) using the Auto WEKA 2.6 tool for accurate classification of different stages of AD. Amir "Ghahnavieh etc. (2019)" suggested a combination of Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) for AD classification. Features extracted from CNN were fed as input to RNN to improve classification accuracy. "Hon & Khan (2017)" utilized the Inception v3 transfer learning network for AD classification. Transfer learning involves leveraging pre-trained models on large datasets to improve performance on smaller datasets. "Fu'adah etc. (2021)" employed the AlexNet architecture for AD classification, using a 75% training and 25% validation split of the datasets.

"Helaly etc. (2022)" proposed a transfer learning model architecture in CNN for the multi-class and binary classification of 2D and 3D medical images in AD. "Wen etc. (2020)" explored four different approaches for AD classification: 3D subject-level, ROI-based, patch-level, and slice-level CNN models. "Oh etc. (2019)" suggested an unsupervised learning approach using a convolutional autoencoder for feature extraction and supervised transfer learning for the classification of AD, normal controls (NC), and mild cognitive impairment (MCI). "Acharya etc. (2021)" employed VGG16, ResNet, and AlexNet transfer learning models to classify AD. "Zhang etc. (2016)" proposed a landmark-based framework to extract features for AD classification. These features were then fed into an SVM classifier. "Rallabandi etc. (2020)" used the FMRIB's Software Library (FSL) for skull stripping, FSL-FAST4 for segmentation, and FreeSurfer for feature extraction from gray matter segmented images. AD classification was performed using the Auto WEKA2.6 ML tool. These studies demonstrate the application of various machine learning techniques and architectures for the classification of AD, aiming to improve early detection and diagnosis of the disease.

Our research contributions are summarized below:

This paper explores the impact of various CNN models and optimizers on AD classification accuracy and suggests effective optimizers for classification tasks.

For classification accuracy, the study compares widely used models (Googlenet, Squeezenet, MobilenetV2) with common optimizers (ADAM, RMSProb, SGDM).

Validation is accomplished by comparing results to those of existing methods. Notably, with a minimum epoch size of 10 and a learning rate of 0.0003, a greater accuracy of 91.34% is achieved.

The remaining sections of this paper are organized in the following manner. Section 2 explores the proposed methodology, including data collection, preprocessing techniques, data augmentation, the optimizer used, and the classifiers employed. Section 3 delves into the results and offers a comparative discussion of the proposed method with other existing methods.

2. Proposed Methodology

The objective of the proposed work is to evaluate the performance of convolutional neural networks (CNNs) using different optimizers for the task of classifying Alzheimer's disease datasets. The study focuses on four pretrained models: AlexNet, SqueezeNet, GoogLeNet, and MobileNetV2.To assess the classification accuracy of these models, three popular optimizers are employed: Root Mean Square Propagation (RMSProp), Adaptive Moment Estimation (ADAM), and Stochastic Gradient Descent (SGD). These optimizers are widely used in deep learning for training neural networks.

The performance evaluation involves training each pretrained model on the Alzheimer's disease dataset and measuring its classification accuracy. Each model is trained using one of the optimizers mentioned above, and their classification accuracy is compared. The classification accuracy metric measures how well the models can correctly classify instances of Alzheimer's disease within the dataset.

By conducting this analysis with different optimizers, the study aims to determine which optimizer yields the highest classification accuracy for each pretrained model. This evaluation helps identify the optimizer that is most suitable for training CNNs on Alzheimer's disease datasets, potentially leading to improved diagnostic capabilities or other applications related to the disease.

2.1 Data Collection

In the proposed work, the datasets used for training and evaluating the CNN models are obtained from the Kaggle database. These datasets consist of various modalities of data related to Alzheimer's disease. The dataset is labeled and divided into four different classes, namely Very Mild Demented, Mild

Demented, Moderately Demented, Non Demented. These classes represent different stages or levels of dementia severity. By classifying the input data into these categories, the CNN models aim to perform Alzheimer's disease classification (AD classification). Datasets are collected from Kaggle Alzheimer's dataset 4 class of images.

The classification task involves training the CNN models using the labeled dataset, where the input data includes various modalities, such as images, clinical features, or other relevant information. The models are trained to learn patterns and features from the input data that can distinguish between the different dementia classes. By utilizing the pretrained models (AlexNet, SqueezeNet, GoogLeNet, and MobileNetV2) and fine-tuning them on the Alzheimer's disease dataset, the models can leverage their prelearned knowledge to improve the classification accuracy for AD classification.

The performance evaluation of the CNN models, as mentioned earlier, involves comparing the classification accuracy achieved by different optimizers (RMSProp, ADAM, and SGD). This analysis helps determine which optimizer performs best for each pretrained model in terms of accurately

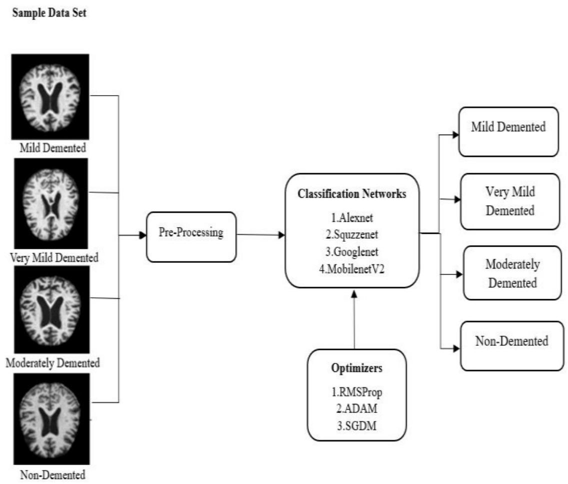


Fig 1. Block Diagram of Proposed Methodology.

classifying the input data into the four dementia classes. Overall, the goal of this proposed work is to leverage CNN models and different optimizers to accurately classify Alzheimer's disease data obtained from the Kaggle database, specifically into the classes of Very Mild Demented, Mild Demented, Moderately Demented, and Non-Demented.

2.2 Preprocessing

In the preprocessing step of image datasets for convolutional neural network (CNN) models, resizing the images is a common practice to ensure compatibility with the input requirements of the models. For AlexNet and SqueezeNet, the input image size is typically resized to 227x227x3. These models were popularized before the widespread adoption of the ImageNet dataset, and this input size was chosen to fit the architecture of these models. On the other hand, GoogLeNet and MobileNetV2, which were developed later, typically expect input images to be resized to 224x224x3. This input size has become a standard for many CNN

2.3 Data Augmentation

To enhance the size of the original datasets, data augmentation techniques are employed to create various versions of the real dataset. Computer vision and Natural Language Processing (NLP) models employ data augmentation techniques to address data scarcity and a lack of sufficient diversity. For Data augmentation generally increase the number of data samples by using various augmented techniques to train a model effectively. To expand the amount of data samples in our proposed study, data augmentation techniques such as reflection, translation, and scaling are applied.

2.4 Classifier

In this proposed work, four pretrained CNN models are used for performance evaluation of AD classification. They are discussed below.

1. AlexNet: Alex Krizhevsky unveiled AlexNet, a deep architecture, in 2012.It consists of eight learned layers, including five convolutional layers with max pooling, followed by fully connected layers. The input image size for AlexNet is 227x227x3 RGB. All layers utilise ReLU (Rectified Linear Unit) as their activation function. AlexNet computes approximately 62.3 million parameters, enabling efficient classification.

2. GoogLeNet: GoogLeNet, proposed by the Google team in 2014, is an architecture with 22 layers designed to improve computational efficiency. The input image size for GoogLeNet is 224x224x3 RGB. GoogLeNet incorporates a 1x1 convolutional layer in the middle, along with global average pooling. It utilizes filter sizes ranging from 1x1 to 5x5, ReLU activation for convolutional layers, dropout for regularization, and a SoftMax classifier. GoogLeNet computes around 7 million parameters for effective classification.

3. SqueezeNet: SqueezeNet is an architecture proposed by researchers from DeepScale, University of California, Berkeley, and Stanford. It aims to provide a 50 times reduction in the number of parameters compared to AlexNet. The input image size for SqueezeNet is 227x227x3 RGB. The architecture starts with a convolutional layer followed by eight fire modules. ReLU is used as the activation function, and softmax is employed in the classifier. SqueezeNet analyzes approximately 1.24 million parameters, offering better classification with reduced computational complexity.

4. MobileNetV2: MobileNetV2 is a neural network architecture proposed by researchers from Google, specifically optimized for mobile devices. It is a 53-layer deep model. The input image size for MobileNetV2 is 224x224x3 RGB. MobileNetV2 employs inverted residual blocks with bottleneck features, distinguishing it from MobileNet. It computes a total of 3.5 million parameters for efficient classification.

These pretrained CNN models provide different architectural variations and parameter counts, enabling researchers to explore their performance in AD classification tasks. The proposed work aims to evaluate and compare the performance of these models using different optimizers, such as SGDM, ADAMT, and RMSProp, to determine the most effective approach for AD classification.

2.5 Optimizer

1. Stochastic Gradient Descent (SGD): SGD is an optimizer commonly used for training neural networks. Instead of computing the gradients for the entire dataset, SGD randomly selects a subset of samples (known as a batch) at each iteration. This approach speeds up the optimization process and allows the network to update its parameters based on a smaller set of data. By iteratively updating the parameters, SGD aims to find the global minimum of the objective function. It is a widely used optimizer due to its simplicity and effectiveness (Haji & Abdulazeez, 2021) (Zaheer & Shaziya, 2019).

2. Adaptive Moment Estimation (ADAM): ADAM is an optimization algorithm that combines the concepts of both SGD and RMSProp. It maintains separate learning rates for each parameter in the network, adapting them over time based on the historical gradients. ADAM incorporates a bias correction mechanism to provide more accurate estimates of the first and second moments of the gradients. This optimizer is known for its ability to handle sparse gradients and works well in practice for a wide range of deep learning tasks (Haji & Abdulazeez, 2021) (Zaheer & Shaziya, 2019).

3. Root Mean Square Propagation (RMSProp): RMSProp is another popular optimizer used in deep learning. It calculates the weight updates based on the running average of squared gradients. By keeping only the current gradient information and eliminating the past gradient information, RMSProp mitigates the influence of older gradients. This helps to address the issue of slow convergence that can occur with SGD. The use of the squared gradients provides a form of adaptive learning rate, allowing the optimizer to adapt the learning rate for each parameter based on the magnitude of the gradients (Haji & Abdulazeez, 2021) (Zaheer & Shaziya, 2019).

These three gradient-based optimizers offer different strategies for updating the network parameters during the training process. By evaluating their performance in the proposed work, can able to determine which optimizer yields the best accuracy for AD classification.

3.Results and Discussion

In this proposed work 90% of image dataset has taken for training and remaining 10% is used for validation. Here Accuracy is considered as an evaluation metric and it’s calculated by below formula,

Accuracy= (True positive+ True Negative)/(True positive+ True Negative+ False Positive+ False Negative)

3.1 Results

Fig 2 represents training progress of classifiers with respective optimizers. The fig 2 shows the training accuracy and loss value.

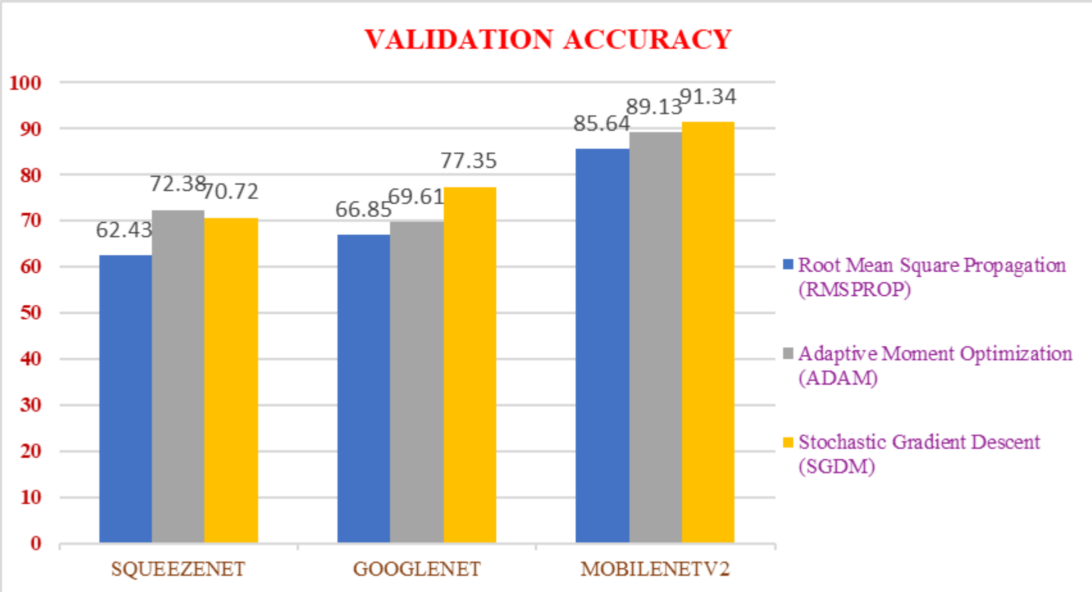


Fig 2. Training progress of CNN models using RMSProp, ADAM AND SGDM optimizers (a) - (l)

3.2 Performance Evaluation

The relative evaluation summary in table 1 shows that MobileNetV2 with the SGDM optimizer outperformed other deep CNN transfer learning models on the AD Kaggle dataset, achieving an accuracy of 91%. The evaluation was conducted using specific hyperparameter settings, including an epoch size of 10, a learning rate of 0.0003, and a batch size of 10. Each epoch consisted of 489 iterations. This indicates that MobileNetV2, a lightweight and efficient CNN architecture, combined with the SGDM optimizer, yielded better results compared to other deep models on the AD Kaggle dataset. Fig 3 represents the graphical sketch of table 1.

Table 1. Accuracy of CNN models using various optimizers

DEEP NEURAL NETWORK	Root Mean Square Propagation (RMSPROP)	Adaptive Moment Optimization (ADAM)	Stochastic Gradient Descent (SGDM)
ALEXNET	57	59	61
SQUEEZENET	62	72	71
GOOGLENET	67	69	77
MOBILENETV2	85	89	**91**

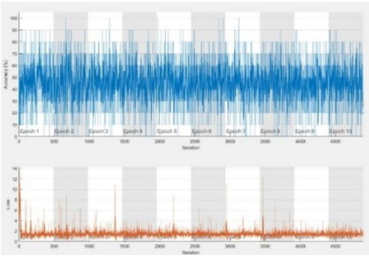
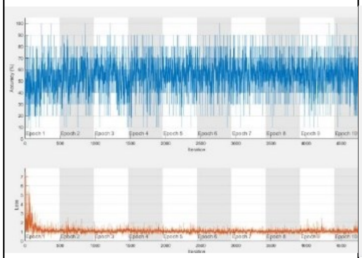
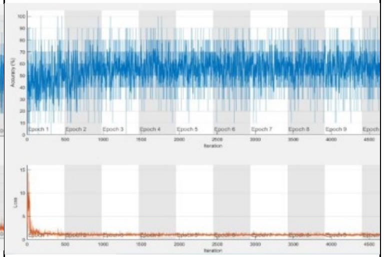
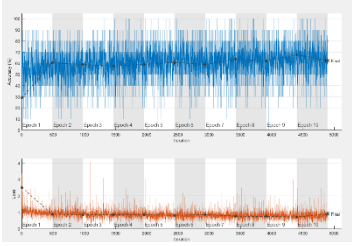
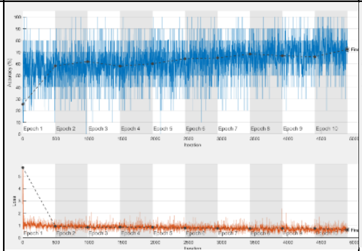
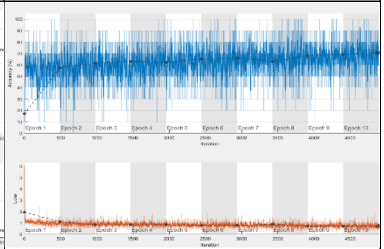
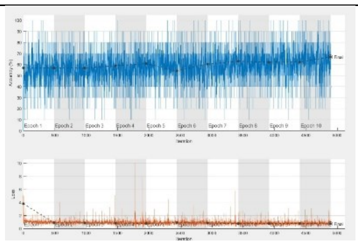
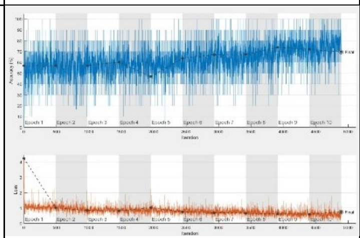
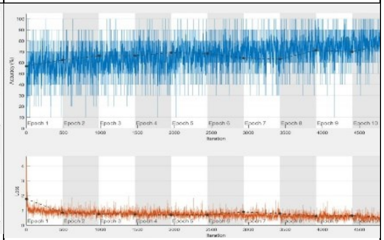
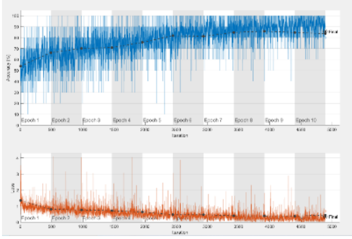
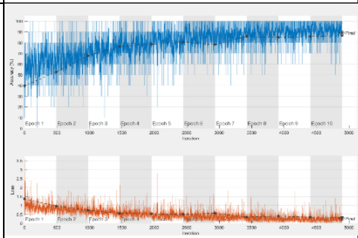
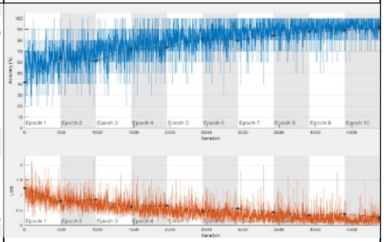
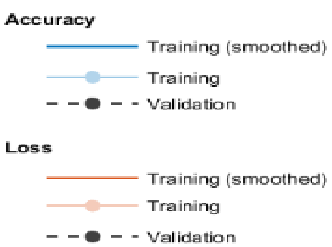
CNN / OPTIMIZERS	Root Mean Square Propagation (RMSPROP)	Adaptive Moment Optimization (ADAM)	Stochastic Gradient Descent (SGDM)
ALEXNET	 (a)	 (b)	 (c)
SQUEEZENET	 (d)	 (e)	 (f)
GOOGLENET	 (g)	 (h)	 (i)
MOBILENETV2	 (j)	 (k)	 (l)

Fig 3. Graphical representation of proposed work validation Accuracies using various optimizer



3.3 Discussion

In contrast to the innovative methodologies investigated, our methodology presents a unique standpoint by utilizing a Mobilenet V2 model with SGDM optimizer for the purpose of Alzheimer's disease (AD) classification. In a previous study, a convolutional neural network (CNN) transfer learning approach was employed on segmented grey matter, resulting in an accuracy of 93.11% (Raza et al, 2023). In contrast, our method achieves a commendable accuracy of 91.31% without the requirement of image segmentation, utilizing an epoch value of 10.

In a further study, a Deep Neural Network (DNN) was utilized with the optimized ADAM optimizer, leading to a notable classification accuracy of 91.29%. The success of this accomplishment was ascribed to the use of Local Binary Pattern (LBP) features-(Ghahnavieh etc.2019), underscoring the efficacy of this methodology.

Table 2. Comaprison of proposed work with existing method

Research	Model	Accuracy (%)
Suresha et al, 2020	DNN with ADAM	91.29
Antony et al, 2022	VGG-16	81
Al-Aiad et al, 2021	VGG-16	70.3
Shruti Pallawi et al,2023	Resnet 50 & Resnet 101 (at epoch 10)	65.82 & 58.69
Shruti Pallawi et al, 2023	InceptionV3 (at epoch 10)	79
Proposed Work	MOBILENETV2 with SGDM	91.34

In a similar manner, the VGG16 model was utilized by the author, resulting in an accuracy rate of 81% (Antony et al,2022). Nevertheless, our approach outperforms the aforementioned outcome by attaining a precision rate of 91.31%. Furthermore, the VGG-16 model, which is a prominent architectural design (Mggdadi et al,2021), exhibited a classification accuracy of 70.3%. This result further emphasizes the progress achieved by our methodology.

Table 1 represents the comparison of our work with existing state of art techniques. Our methodology distinguishes itself by utilizing a Mobilenet V2 model and SGDM optimizer, resulting in a noteworthy accuracy rate of 91.31% without the need for image segmentation. This statement underscores the strength and reliability of our methodology, as well as its capacity to improve the effectiveness of AD classification. Ultimately, it has the potential to advance the frontiers of accuracy and innovation within this discipline.

4.Conclusion

This paper provides an extensive analysis of four conventional pretrained CNN models in the context of Alzheimer's disease (AD) classification. The focus of the analysis is on evaluating the performance of different gradient-based optimizers, including SGDM, ADAMT, and RMSProp, to enhance the CNN models. The objective of the study is to demonstrate the effectiveness of various training optimizer techniques in improving the performance of CNN models for AD classification. The comparative evaluation conducted in the paper reveals that the SGDM optimizer achieved the highest accuracy of 91% for AD classification among the optimizers tested. The findings presented in the paper can be valuable for researchers and practitioners in the field of deep learning and medical image processing. By considering the comparative evaluation of deep CNN models and optimizers, researchers can make informed decisions regarding the selection of appropriate models and optimizers for achieving optimum AD classification performance. It's worth noting that the specific performance and accuracy values mentioned in the paper are specific to the experiments conducted by the authors. The performance of deep learning models can vary depending on factors such as the dataset, hyperparameter settings, and specific task requirements. Therefore, it's important for researchers to conduct their own evaluations and consider the specific context of their work when selecting models and optimizers. İn future optimization algorithm can be applied to hypertune the deep network parameters also segmentation technique may be used for better classification.

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