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RESEARCH ARTICLE

ALZHEIMER DISEASE DETECTION VIA DEEP LEARNING BASED SHUFFLE NETWORK

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Abstract – Alzheimer's disease (AD) is a progressive neuro degenerative ailment that decimates the brain memory. The early stage of Alzheimer's is mild cognitive impairment (MCI) and it is hardly possible to diagnosis. Artificial intelligence (AI) has proliferated in recent years across all scientific disciplines. The early detection of AD is now more accurate and precise thanks to the application of AI in medicine. In the proposed study, introducing a novel technique named ShuffleNet for prognosticating dementia, which is intended to assist doctors in diagnosing AD. Magnetic resonance imaging (MRI) was collected from Alzheimer's disease Neuroimaging Initiative-3 (ADNI-3) and pre-processed using Histogram Equalization (HE). ShuffleNet a deep neural network combined with the leaky ReLU was used for extracting the surface features from brain MRI. Finally, the proposed system's effectiveness was demonstrated by the correct classification that was acquired using the multi-layered perceptron (MLP) classifier. When compared to CNN's current networks, the suggested model's findings are the best and most accurate. This model yields the sensitivity range of 98.22%, specificity range of 98.75% and accuracy rate of 99.72% respectively with the minimal computational cost.

***Keywords** – Alzheimer Disease, Artificial Intelligence, ShuffleNet, Learning, Brain Magnetic Resonance Images*

1. INTRODUCTION

A common brain condition that primarily affects elderly persons is Alzheimer's disease (AD). After heart disease, cancer, and brain hemorrhage, it ranks as the fourth most common cause of death around the world [1]. Each year, a reported 10 million infection cases occur. From a neurological standpoint, AD is a chronic neurodegenerative condition that damages brain tissue and induces neuronal cell death. As a result, the patient slowly loses cognitive function and memory, a condition called senile dementia.

Dementia affects over 50 million people globally, 60% of whom living in low- and middle-income nations. 5-8% of people over 60 in the general society currently have dementia [1]. By 2030, 82 million people will have dementia, and by 2050, 152 million people will have dementia, according to projections. The majority of this growth may be traced to the rise in dementia prevalence in developing and middle-income countries.

Additionally, Alzheimer's disease impairs a patient's capacity to talk, write, and read on a daily basis as well as their ability to recognise friends and family. He advances through the early, intermediate cognitive, and late phases of Alzheimer's disease (AD). People in the medium cognitive stage respond fiercely, but patients in the late stage have heart failure and severe respiratory dysfunction [2].

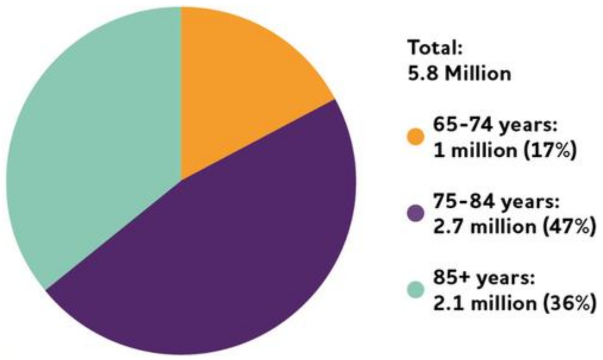


Figure 1. Different age of peoples with Alzheimer's Dementia

Estimates show that 5.8 million Americans 65 and older suffer from dementia connected to Alzheimer's. 80 percent of people are above 75. One in ten women over the age of 65 who have the condition do so. More people develop Alzheimer's disease as they age. According to Figure 1, Alzheimer's disease affects 3% of persons in the 65–74 age group, 17% of people in the 75–84 age group, and 32% of people in the 85–plus age group. Alzheimer's dementia can affect people younger than 65, although it is far less likely to do so and it is not known how frequently it does.

The shuffle-ADD method has been proposed to predict prognosis in dementia to assist physicians in diagnosing AD. The main contributions of this work are:

- Magnetic resonance imaging (MRI) was acquired by the Alzheimer's Disease Neuroimaging Initiative 3 (ADNI-3) and preprocessed using histogram equalization.
- Combined ShuffleNet deep neural network with his Leaky ReLU to extract surface features from brain MRIs.
- Multilayer Perceptron Classifier (MLP) to prove the efficiency of the proposed system. The rest of this work is organized as follows.

A review of the literature is given in Section II. In Section III, the recommended Shuffle-ADD method is explained. Section IV presents the experimental results, while Section V summarizes the contributions.

2. RELATED WORK

Researchers have recently developed a number of deep learning approaches, mostly to increase the precision with which Alzheimer disease can be identified using brain MRI. There have been numerous studies in the literature attempting to develop automated algorithms to detect morphological and functional lesions in the brain associated with AD using various deep and machine learning methods. Some of those research works are briefly discussed in this section.

In 2023, Balaji, *et al* [3] proposed a hybrid deep learning technique for Alzheimer's disease early detection. They combined MRI and PET with multimodal imaging, convolutional neural networks, and long-term short-term memory methods. The proposed model's accuracy improved to 98.5%.

In 2023, Marwa, *et al* [4] develop a deep learning-based pipeline for precise AD stage classification and diagnosis. They employed 2D T1-weighted magnetic resonance imaging (MR) brain pictures and convolutional neural network (CNN) architecture. The next step is to divide MCI into three groups: very mild dementia (VMD), mild dementia (MD), and moderate dementia (MoD). stage before AD. The accuracy rate of the suggested model is 99.68%.

In 2021, Murugan, *et al* [5] proposed the accuracy of AD classification is considerably increased by using the CNN approach to extract features. In order to precisely and visually display each individual's risk of AD, the proposed model builds high resolution (HR) disease probability maps from regional brain regions to multi-layered perceptrons. The proposed model is 97% accurate.

In 2022, Ghazal, T.M, *et al* [6] Brain MRI was used to classify the pictures into four stages: mild dementia (MD), moderate dementia (MOD), non-dementia (ND), and very mild dementia (VMD). The suggested transfer learning on multi-class categorization using brain MRI. The accuracy of the suggested system model is 91.70%.

In 2022, Nguyen, D,*et al* [7] proposed an approach to ensemble learning that blends machine learning and deep learning. The Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset of brain MRI images was used to train and evaluate the method [8-10]. The proposed system model has an accuracy of 96.2% [11-15].

3. PORPOSED MODELLING

In this paper Magnetic resonance imaging (MRI) is collect from Alzheimer’s Disease Neuroimaging Initiative-3 (ADNI-3) and it is pre-process using histogram equalization. The output is sent to the ShuffleNet deep neural network combined with the leaky ReLU. It is use for extracting the surface features from brain MRI and the multi-layered perceptron (MLP) classifier, which proves the efficiency of the Shuffle-ADD.

3.1. Preprocessing

The Magnetic resonance image (MRI) is sent to the preprocessing unit. Preprocessing is a great way to enhance the quality of photographs and prepare them for analysis and additional processing. Noise reduction, contrast improvement, image scaling, color correction, segmentation, feature extraction, and other effective image preparation methods are available.

3.1.1. Data Augmentation

The data augmentation component receives a magnetic resonance image (MRI) as input and process it. A technique called data augmentation makes new learning data out of old learning data. Picture data augmentation, which comprises creating modified versions of training data set pictures that belong to the same class as the original image, is perhaps the most well-known type of data augmentation.

Techniques for image modification used in transformation include shift, mirroring, and zooming.

Random picture flips, crops, rotations, stretches, and zooms are examples of geometric image transformations. Additionally, brightness, contrast, and RGB color channels are all modified at random by colorspace conversion. Kernel filters sporadically alter an image's sharpness or blurriness. Particular parts of the original image are randomly deleted. Multiple photos are blended when you merge them.

3.1.2. Histogram Equalization

The histogram equalization process equalizes the digitalized input image (MRI). A contrast enhancing method that works well on practically any kind of image is histogram equalization. By altering the intensity histogram, contemporary techniques like histogram equalisation alter the dynamic range and contrast of a picture.

The Histogram Modelling operator, in contrast to the Contrast Stretch operator, transforms the pixel intensity values in the input and output images using non-linear and non-monotonic transfer functions.

An optimized histogram.

P(n) = total number of pixels / number of pixels with strength

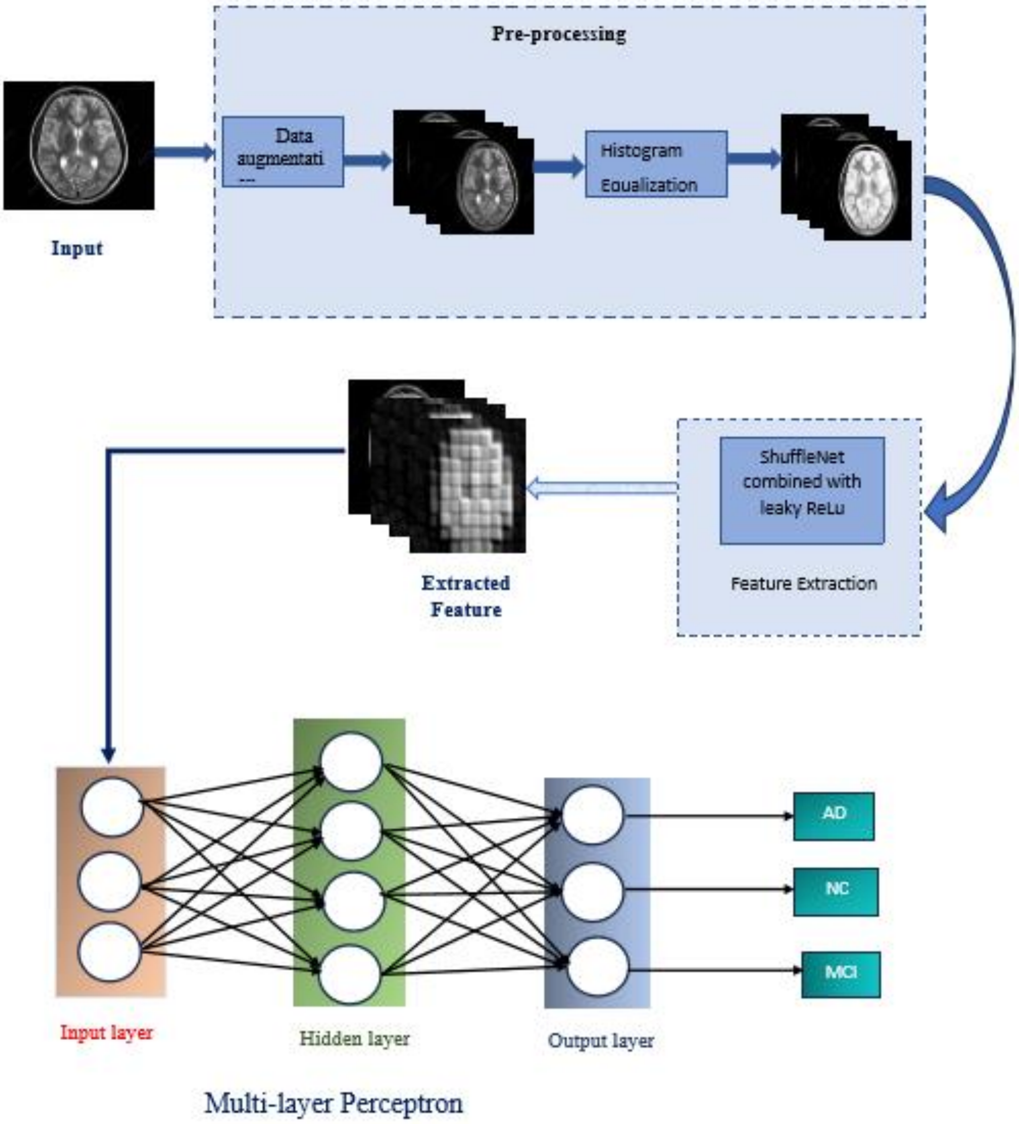


Figure 2. Proposed method working architecture

3.2. ShuffleNet

Shuffle-ADD was employed in the suggested study to attain improved accuracy with less processing. Use the Shuffle-ADD model in accordance with your hardware resources for computing. Figure 3 depicts the framework's architecture. The suggested model has 50 learnable layers, making it more complex than a typical CNN. With this architecture, accuracy is maintained while computational costs are minimized thanks to pointwise group convolution and channel shuffling. A 1x1 kernel, or a kernel that iterates over each point, is the kernel used in a pointwise convolution. This kernel's depth reflects how many channels the input image has. Depthwise separable folds are an effective type of folds that may be made by combining this with depth folding.

In Shuffle-ADD, magnetic resonance image preprocessing is carried out with 10-150 MFLOPs of processing power, Shuffle-ADD is thought to be a very computationally efficient CNN architecture created for mobile devices. A convolutional neural network designed for mobile devices with very limited processing power, Shuffle-ADD uses point-wise group convolution and channel shuffle to lower compute expenses while maintaining accuracy.

Our model accepts a 224×224 input image (magnetic resonance image) for processing as its first layer's input. The convolutional layer uses 24 kernels (filters) of size 3×3 and step size 2 ×2 to extract features from the 224×224 input picture in order to create the feature map.

The feature map produced by the convolutional layer is calculated as

$$A\ (l, m) = (B \times C)\ (l, m) = \sum_a \sum_b B(b, a) C(l - b, m - a))$$

s indicates the feature map output, *i* indicate image input, then *C* indicate the kernel of the convolution layer. After the input image has undergone convolutional processes, the size of the output size o=((l−v) +2t)/(u+1) is produced, where *l* indicate input, *t* means padding, *v* indicate kernel size, and u indicate steps.

The output feature map of the first convolutional layer is sent to the ShuffleNet. unit with a shift (stride) of 2X2. The

ShuffleNet unit consists of two 1 1 pointwise group convolutions and three 3X3 depthwise convolutions, totalling three convolutional operations. The BN, ReLU activation function, and channel shuffle operation come after the first pointwise group convolution.

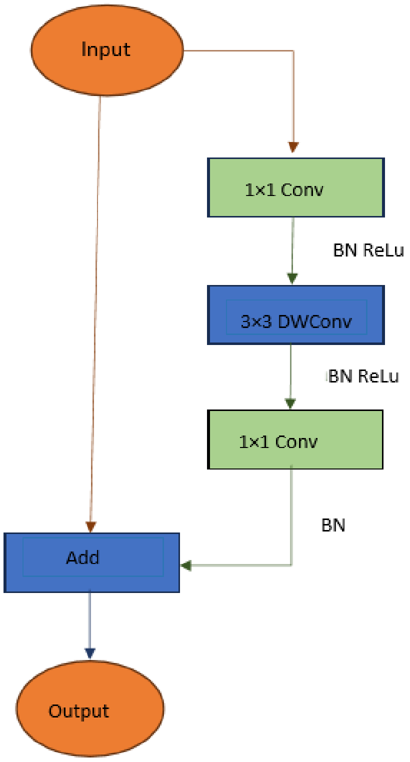


Figure 3. ShuffleNet block diagram

3.3. Multi-layer Perceptron

A multi-layer perceptron (MLP) receives the result of the extracted feature extraction as input. A feedforward neural network extension is MLP. It has three different kinds of layers, as seen in Figure 2: input layer, output layer, and hidden layer. The input layer is where the input signal for processing is received. Utilizing multi-layer perceptrons as classifiers for challenges involving pattern recognition.

The process of extracting a set of characteristics from an object to be classed and using those features to identify the object's class is a typical classification problem. Features in image recognition that are connected to an object's shape include length to width ratio, absolute size, and others. A set of characteristics for a particular item might be thought of as a vector, for example. The feature vector is then analysed to determine the class of each item. A collection of feature vectors with a predetermined categorization are frequently used as the starting point for constructing and testing a classifier. As was already indicated, the ideal features for recognition are not always understood. Additionally, the design set's size must increase as more features are added.

Which features should be employed in the classification problem is strongly related to how multi-layer perceptrons handle wasted input. Less features should be used in general to achieve high classification accuracy. Choosing the ideal selection of features for categorization is the issue. Different properties are accessible depending on the sensor that was used to display the scene, including: B. Aspect ratio, brightness, edge pixels to total pixels, and contrast ratio.

4. RESULTS AND DISCUSSIONS

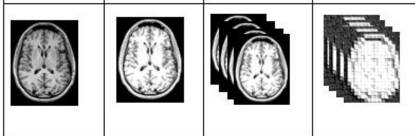
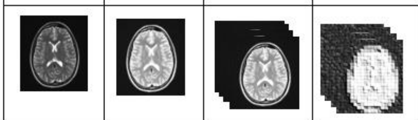
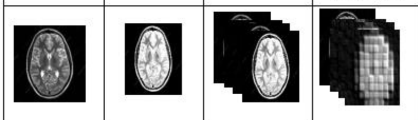
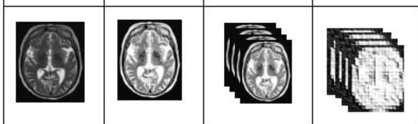
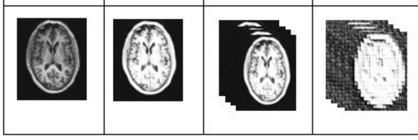
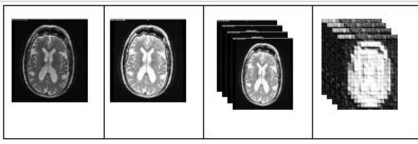
In the research paper, the experimental setting was created using MATLAB 2019b. In this examination, the MRI scans from ADNI-3 datasets was used for detecting AD in earlier stages. The efficiency of the proposed Shuffle-ADD model has been evaluated using the specific parameters. Furthermore, the evaluation of the proposed Shuffle-ADD was compared with classic ML models is also provided in this section.

A data set (or dataset) is a group of related pieces of information. When working with tabular data, a data set refers to one or more database tables, with each row denoting a particular record and each column denoting a particular variable. An item's value for each member of the dataset for each variable, such as size and weight, is listed in a dataset. A record can also be a group of papers or files.

4.1. Performance Analysis

In this section, the efficiency valuation was determined using accuracy, f1 score, precision, specificity, and sensitivity (recall). Experimental results of proposed network based on the MRI images shown in Table 1.

Table 1. Experimental results of proposed network based on the MRI images

Input	Pre-processing	Augmentation	Feature extraction	Classification
				Normal
				Normal
				Alzheimer Disease
				Alzheimer Disease
				Mild cognitive impairment (MCI)
				Mild cognitive impairment (MCI)

The specificity is defined as the proportion of recovered true positive samples from the raw samples was gauged. A measurement of the patient & sickness status is the sensitivity or recall. By classifying the sample MRI images detected as true positives in the patients, it is utilised to assess the accuracy of the outcomes. Some of the parameters are illustrated in equations. where indicates true positives and negatives of the MRI images, and signifies false positives and negatives of the MRI images. The efficiency of the proposed Shuffle-ADD was analysed and it is depicted in Table 2.

Table 2. Performance Analysis of Proposed Shuffle-ADD

Parameter	Accuracy	Specificity	preception	Recall	F1 Score
Normal	99.66	97.47	98.37	98.96	98.08
Alzheimer Disease	99.76	98.16	99.89	98.07	99.53
Mild cognitive impairment (MCI)	97.74	99.02	97.98	99.69	97.98

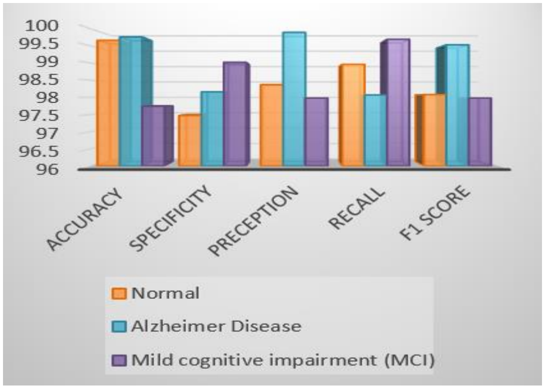


Figure 4. Performance analysis of proposed Shuffle-ADD based on the system of measurement

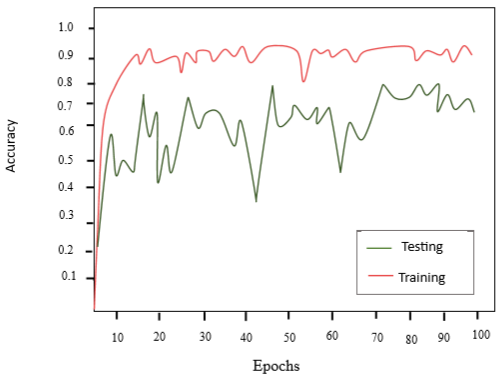


Figure 5. Accuracy curve for proposed Shuffle-ADD

Accuracy curve for proposed Shuffle-ADD SHOWN IN Figure 5. The F1 score, specificity, precision, sensitivity, and accuracy were the key characteristics used to evaluate the effectiveness of the suggested Shuffle-ADD. Table.3 shows the performance evaluation based on the datasets for normal, AD, and MCI. The suggested ShuffleNet successfully classifies NC, AD, and MCI with high accuracy of 99.70%, 99.76%, and 97.70%, respectively. When identifying the normal class as opposed to the abnormal class, this model achieves good accuracy. Figure 4 shows a visual representation of the suggested Shuffle-ADD's performance analysis. Loss curve for proposed Shuffle-ADD shown in Figure 6.

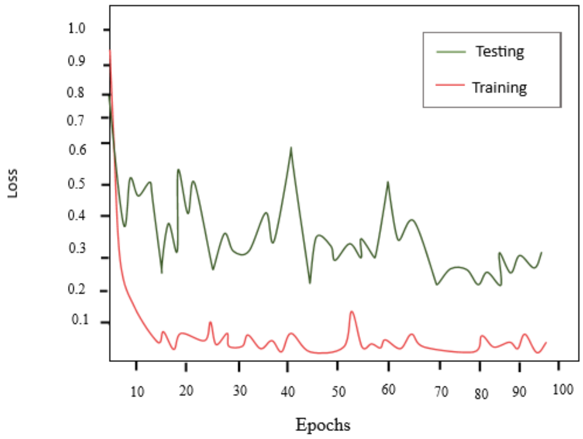


Figure 6. Loss curve for proposed Shuffle-ADD

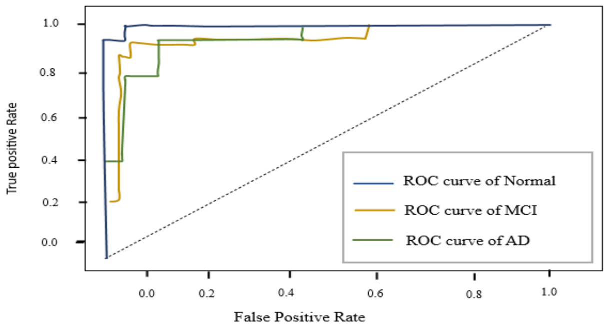


Figure 7. ROC curve of the proposed Shuffle-ADD

Figure 7 shows the Receiver Operating Characteristic (ROC) curve produced for obtained MRI datasets. For the three classes, the suggested Shuffle-ADD achieves a higher Area Under ROC Curve (AUC) of 0.908, which was calculated using True and False positive rate parameters.

4.2. Comparative Analysis

The competence of ML classifiers was estimated for evaluating the fallouts of the proposed Shuffle-ADD obtains better accuracy.

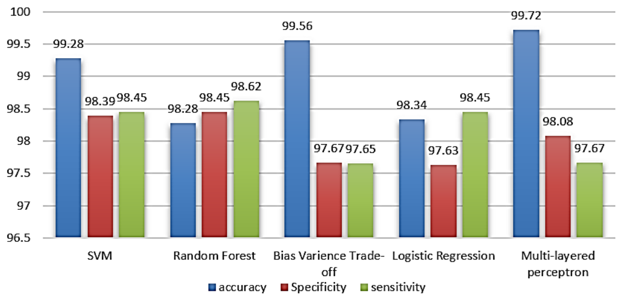


Figure 8. Performance comparison of SVM, Random Forest, Bias Varience Trade-off, Logistic Regression, MLP

The comparative assessment was performed between the proposed Shuffle Net and four ML networks SVM, Random

Forest, Bias Varience Trade-off,Logistic Regression. The performance assessment was carried out using sensitivity, specificity, and accuracy of each ML methods. The accuracy of the proposed Shuffle-ADD is 99.72%, which is greater than the classical ML methods. The performance analysis is shown below figure.8. Accuracy comparison of proposed and state-of-art methods shown in Table 4.

Table 3. Performance comparison of different ML networks

Parameters	accuracy	Specificity	perception	Recall	F1 Score
SVM	99.28	98.39	98.45	98.08	97.45
Random Forest	98.28	98.45	98.62	98.64	98.08
Bias Varience Trade-off	99.56	97.67	97.65	98.27	98.45
Logistic Regression	98.34	97.63	98.45	97.38	97.07
Multi-layered perceptron	99.72	98.08	97.67	97.79	98.59

Table 4. Accuracy comparison of proposed and state-of-art methods

Authors & year	Methods	Accuracy (%)
Balaji,P, *et al*[3],2023	CNN with LSTM Algorithm	98.5
Marwa,*et al*[4],(2023)	CNN	99.68
Murugan,s,*et al*[4],(2021)	CNN	97
Ghazal, T.M,*et al*[6],(2022)	Transfer Learning Method	91.70
Nguyen, D,*et al*[7],(2022)	Ensemble Learning Method	96.2
Proposed model	Shuffle-ADD	99.72

From this experiment the Multi layered perceptron accuracy is high compared to the other network such as SVM, Random Forest, Bias Varience Trade-off, Logistic Regression, MLP. The acuuracy level is 99.72%. It detects the small variations in the Magnetic Resonance Image (MRI) to diagnosis Alzheimer Disease (AD).

5. CONCLUSION

In this paper, the experimental setting was created using MATLAB 2019b. In this paper Shuffle-ADD, the MRI image from ADNI-3 Alzheimer Disease Neuro-imaging Initiative (ADNI-3) datasets was used for detecting AD in earlier stages. The Multi-Layer Perceptron classify the Alzheimer Disease into normal, mild congnitive impairment and Alzheimer Disease that helps to predict the disease earlier. The proposed Shuffle-ADD obtains the accuracy of 98.08%, 97.25%, and 98.44% for classifying NC, MCI and AD respectively. The proposed Shuffle-ADD progresses the overall accuracy of 1.67%, 0.04%,8.02% and 3.70% better than CNN with LSTM Algorithm, CNN, Transfer Learning Method, Ensemble Learning Method respectively. In future, the accuracy of the proposed Shuffle-ADD will be progresses in order to precisely detects the grades of AD for improving the accuracy in early diagnosis of Alzheimer disease in its early stages.

CONFLICTS OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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