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Designing an Intelligent System for Predicting Alzheimer's disease

WASAN AHMED ALI
Department of computer science, College of Science, University of Diyala, Iraq
Corresponding author: Wasan Ahmed Ali (e-mail: wasanahmed83@gmail.com).

ABSTRACT Alzheimer's disease (AD) is a degenerative progressive disorder that affects the brain's neurons and nerve cells, causing behavioral changes, memory loss, language skills, and thinking. It is a neurological condition with an exponentially increasing incidence rate, primarily affecting adults over 65. Contrary to popular belief, AD is not a normal aspect of aging and is the most prevalent type of dementia. In this work, CNN, Densenet169, and the Hybrid convolution recurrent neural network approach are used to detect Alzheimer's disease at an early stage. Data augmentation is utilized at preprocessing step to handle the small size of the dataset. The Hybrid CNN-RNN network design comprises convolution layers followed by a recurrent neural network (RNN). The combined model uses the RNN to extract relationships from MRI images and to account for temporal dependencies of the images during classification. Three algorithms are used for classifying AD and comparing their results. We have tested the model on MRI dataset. According to the results, the proposed CNN algorithm achieved higher accuracy than the Densenet169 and the hybrid Convolution-Recurrent Neural Network.

KEYWORDS Densenet169; Convolution neural network; Alzheimer disease prediction; deep learning; Transfer learning.

I. INTRODUCTION

AD is a long-term neurodegenerative condition. The abnormal accumulation of neurofibrillary tangles and amyloid plaques in the brain that characterize this irreversible condition causes a progressive deterioration in memory, thinking, and language abilities, as well as behavioral disturbances. By 2050, 11 million to 16 million old peoples may have Alzheimer's disease due to longer life expectancies [1]. There is currently no effective treatment for this illness, as far as we know. However, early identification is crucial for prompt therapy and reversing development. The likelihood of the disease progressing from mild cognitive impairment (MCI) to AD may also be predicted, which is crucial. MCI is a stage between age-related cognitive deterioration and Alzheimer's disease. Identifying MCI patients who are at high risk of developing AD is crucial for effective therapy. As a result, progression detection and AD diagnosis involve multiple stages. Physicians first identify the patient's category (MCI or AD). Second, they carefully examine patient biomarkers to ascertain whether MCI is progressing toward AD [2].

The first parts of the brain that may be impacted can be seen on an MRI (Magnetic resonance imaging) and include the hippocampal lobe and medial temporal gyrus. In the brain, the hippocampus is a deep structure that plays a role in memory and decision-making. Among its symptoms are neuron loss and synapses in the temporal, parietal, and cortical lobes and involvement of the cingulate gyrus [3]. AD is primarily diagnosed based on clinical evidence at various stages. Depending on the severity of cognitive impairment, it is divided into dementia-stage, mild, and preclinical categories. Periodic short-term memory loss and a relative sparing of long-term memory are the primary symptoms[4].

Imaging tests are carried out to rule out other potential causes of dementia, such as cerebrovascular, vitamin B12 deficiency, syphilis disease, and many more. According to a volumetric MRI (Magnetic resonance imaging), the medial temporal lobe has shrunk. Shorter brain areas of the medial temporal and parietal lobe are utilized to map patterns of dysfunction using functional brain imaging techniques like PET (Positron Emission Tomography), fMRI, and SPECT (single-photon emission computerized tomography). According to research[5][6], clinical studies need to target individuals in earlier stages before there is obvious brain atrophy. But the problem is detecting the illness at an early stage.

In this paper, three models are proposed to detect Alzheimer's disease, the first is based on simple CNN with two hidden layers, the second is based on Densenet169 with transfer learning, and the third is based on hybrid CNN-RNN. The models are conducted on an MRI dataset obtained from

KAGGLE repository. The model based on CNN achieved an accuracy of 99%, whereas the model based on Densenet169 and transfer learning achieved an accuracy of 88.7%, and the hybrid CNN-RNN model accuracy is 93.94%. The results proved that the proposed CNN model outperformed the Densenet169 and hybrid CNN-RNN model. That means it can build an accurate model with a less complex model.

This work is aim to design a less complex model to accurately predict Alzheimer's disease. The remaining of the paper is structured as follows: section.2 illustrates related work, section 3 illustrates tools and method, Section.4 illustrates the proposed model, section.5 presents Results and discussion, and finally the conclusion in section6.

II. RELATED WORK

Researchers have long used several machine-based techniques to identify Alzheimer's disease just from MRI data. The first step taken by researchers was to create testable biomarkers. A biomarker is a crucial indicator of biological health. The hippocampal area has been employed by doctors as a significant biomarker and has been shown to provide a highly accurate AD diagnosis. However, the hippocampus volume is insufficient to quantify the development of MCI into Alzheimer's disease[7]. The progression of the disease is also influenced by additional parameters such as cortical areas and thickness. Given the characteristics of space in MRI scans, research tools and extensive research techniques are frequently suited for integrating those divisive characteristics[8]. Richer and more reliable feature representation is made possible by deep learning, a branch of machine learning.

Ref[9] constructed a prediction model using a least absolute shrinkage selection operator(LASSO) regression analysis to identify the best predictor variables, and the prediction model is build based on multivariate logistic regression.

Ref[10] constructed a prediction model using multimodal RNN by combining longitudinal cerebrospinal fluid (CSF) and cognitive performance biomarkers collected from ADNI with cross-sectional neuroimaging biomarkers at baseline, Lee et al. created an integrated framework that had an accuracy of 81%.

Ref [11] enhanced learning procedure in which the weight factor of DNN is incorporated with CNN for dealing with multimodal heterogeneous information and achieved an accuracy of 92.5%.

Ref[12] designed an image fusion approach to fuse MRI with PET images from AD patients. Then employed 3D CNN to estimate the image fusion approach effectiveness in both multi-classification tasks and dichotomous.

Ref[13] is presented a model for early diagnosis of AD depending MRI by utilizing the ConvNets to automatically fuse and transform the ADNI into the BIDS standard for classifying various MRI data of Alzheimer's subjects from healthy controls.

Ref [14] a multimodal image fusion method to fuse MRI neuroimages with a modular set of image preprocessing procedures was introduced. Additionally, AD biomarkers are captured in fused images and used to train a 3D convolutional neural network to learn generic features, producing richer multimodal feature data.

III. METHODOLOGY

A. DATASET

The KAGGLE Alzheimer's image database is used for the research in this paper[15]. Four different MRI image types, each with a resolution of 176 208, are included in the KAGGLE Alzheimer's dataset: non-AD (3,200 images), very mild AD (2,240 images), mild AD (896 photos), and moderate AD (64 images). Patient status is not explicitly described in the KAGGLE Alzheimer's dataset. Examples of images from the KAGGLE Alzheimer's dataset are shown in Figure 1. The dataset comprises two files, Training, and Testing, with a total of about 5000 photos. Each divided into four classes: mild, very mild, non-demented, and moderate demented Alzheimer's disease.

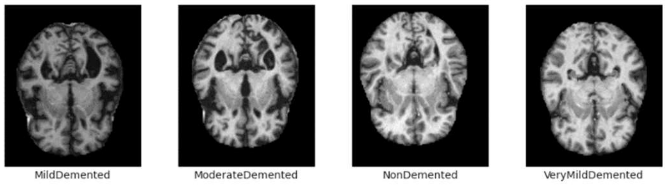

Figure 1. Example images of Kaggle Alzheimer's dataset

B. DATA AUGMENTATION

Data augmentation methods are frequently employed to increase the database's dimension because public image-labeled databases typically have a small dimension. Because they have a low computational complexity, geometric data augmentation methods are the most used. Simard et al. showed the advantages of using geometric changes, such as skewing, translations, and rotations, of training images for data augmentation [16].

C. TRANSFER LEARNING

A research effort called ImageNet aims to create a sizable library of images with annotations, such as labels for the images. Pretrained models are already trained on ImageNet like Densenet169, InceptionV1 and V2, which consists of disparate image categories. These models were created from scratch and were trained using powerful GPUs on millions of photos belonging to many different image classes. Due to the model's extensive training data, it has developed a strong representation of low-level features. These features, including edges, shapes, rotations, and illumination, can be shared to facilitate the transfer of information and serve as a feature extractor for new images in various computer vision challenges[17].

The characteristics and data of most machine learning models change over time, which requires re-creating the model. Machine-learning information previously obtained can often apply to similar tasks. Instead of rebuilding the models, transfer learning reuses the data and model rather than rebuilding them from scratch. Additionally, the model development time will reduce dramatically and improve the isolated learning model's effectiveness [18].

D. CONVOLUTION NEURAL NETWORKS (CNN)

One of the most well-liked models, CNN has demonstrated excellent performance on numerous picture classification issues in the agriculture sector. By identifying strong features in the images and minimizing the gradient vanishing problem, the concept of sharing weights in DCNN creates an effective image categorization. Figure 2 illustrates the construction of a typical CNN [19].

A pooling layer, a fully connected layer, and the convolution layer all make up CNN's architecture. The primary function of the convolutional layer, which serves as a filter, is to extract features from the photos of insects. The pooling layer, which downscales and preserves the most crucial information in the insect images, comes after the convolutional layer. This layer minimizes the number of parameters and the spatial dimension of representation, which improves the model's efficiency by preventing over fitting. The last layer, fully connected, uses a softmax activation function to extract the high-level features from photos of insects and classifies them according to multiple labels [20].

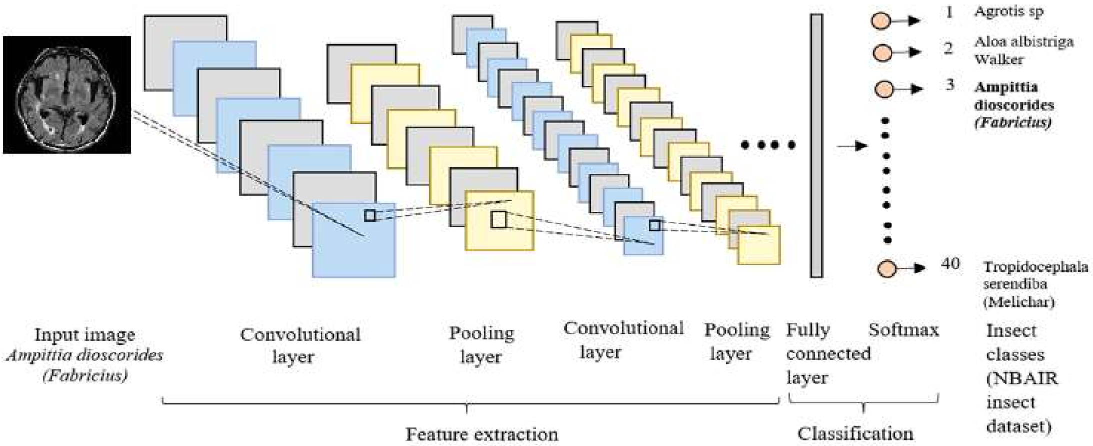

Figure 2. Basic CNN architecture

E. DENSENET

The DenseNets was put forth in 2017 at the CVPR conference[21]. The goal was to build a deeper convolution network, which would be more efficient and accurate to train since it would have shorter connections between the layers closest to the input and those closest to the output. In contrast to ResNet, using skip-connections to avoid the nonlinear transformation, DenseNet adds a direct connection from each layer to any succeeding layer[22]. Table 1 illustrates the architecture of the DenseNet169 model with the imageNet pre-trained weight[22][23].

Table 1. Architecture of Densenet169 model for imagenet [23]

Layers	Output Size	DenseNet 169
Convolution	112×112	7×7 conv, stride 2
Pooling	56×56	3×3 max pool, stride 2
Dense Block (1)	56×56	$\begin{bmatrix} 1\times 1 \text{ conv} \\ 3\times 3 \text{ conv} \end{bmatrix} \times 6$
Transition Layer (1)	56×56	1×1 conv
	28×28	2×2 average pool, stride 2
Dense Block (2)	28×28	$\begin{bmatrix} 1\times 1 \text{ conv} \\ 3\times 3 \text{ conv} \end{bmatrix} \times 12$
Transition Layer (2)	28×28	1×1 conv
	14×14	2×2 average pool, stride 2
Dense Block (3)	14×14	$\begin{bmatrix} 1\times 1 \text{ conv} \\ 3\times 3 \text{ conv} \end{bmatrix} \times 32$
Transition Layer (3)	14×14	1×1 conv
	7×7	2×2 average pool, stride 2
Dense Block (4)	7×7	$\begin{bmatrix} 1\times 1 \text{ conv} \\ 3\times 3 \text{ conv} \end{bmatrix} \times 32$
Classification Layer	1×1	7×7 global average pool
	1000	1000D fully-connected, softmax

F. RECURRENT NEURAL NETWORK

Numerous theoretical and practical research works on this type of RNN have been published since the initial 1997 LSTM study[24]. Many of which report on the remarkable results attained across a wide range of application fields where the data is sequential. Speech-to-text transcription, Language modeling, machine translation, and other applications have benefited significantly from the LSTM network.

Some readers in professional and academic settings choose to learn about the LSTM to evaluate its applicability to their research or practical use case. This decision is motivated by the impressive benchmarks reported in the literature. Numerous RNN and LSTM network topologies have effective, production-ready versions available in all significant open-source machine learning frameworks[25].

IV. PROPOSED MODEL IMPLEMENTATION

In this paper, Alzheimer's disease prediction is perform in a three scenario: the first is based on CNN, the second on Densenet169 with transfer learning, and the third is based on the hybrid CNN and RNN.

Figure 3 illustrates the architecture of the proposed method design. In this work, three algorithms are used to predict Alzheimer's disease and they are compared with each other based on accuracy and loss. The image data is first normalized using scaling. Then, different data augmentation methods are performed to augment the training dataset: vertical flip, random rotation, and horizontal flip. By creating new but distinct versions of the original images, these strategies aim to boost the amount of training dataset for the model training phase.

The models conduct on the MRI dataset obtained from the KAGGLE repository. CNN, Densenet169, and Hybrid CNN and RNN models are implemented using the Keras module of the Tensorflow Flow open-source library for deep-learning models. The models are trained on these images to build the AD detection model.

A. CONVOLUTION NEURAL NETWORKS

The summary of the CNN model employed is illustrated in figure.4. The batch size is 32, the number of epoch is 50, and image size is (128x128). The dataset contains 6400 images belong to four classes (Mild, moderate, non, and very mild), 80% is used for training and 20% is used for testing.

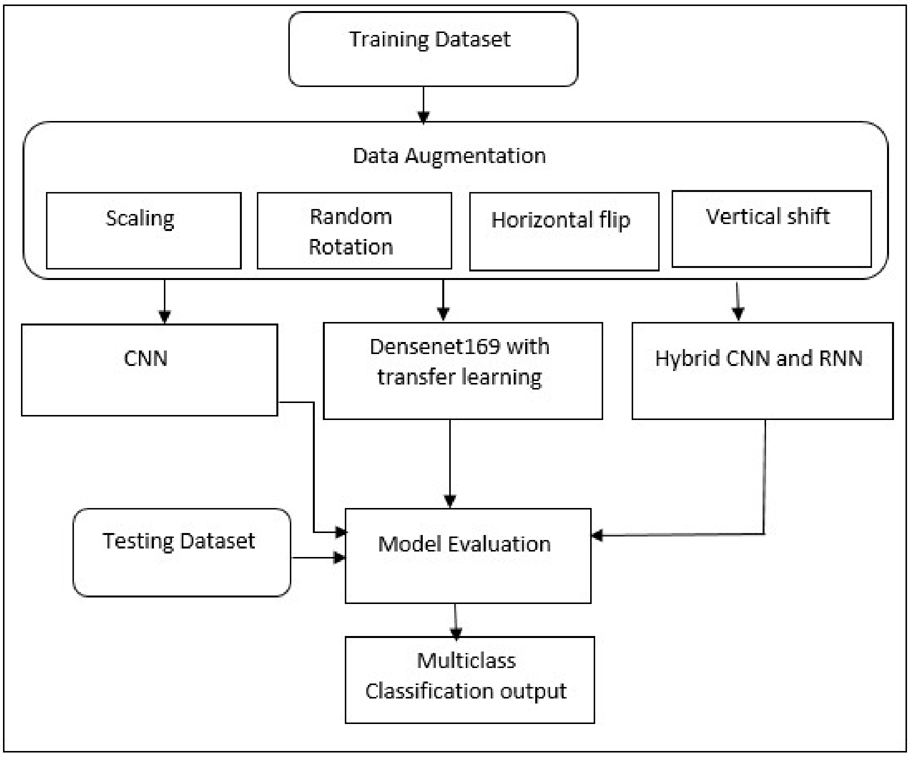

Figure 3. Proposed model design

B. DENSENET 169 NETWORK

One of the most important models used by the Densenet group to classify images is Densenet169. The better size and accuracy of the model contribute to its relative popularity. It is an output classifier object for the Imagenet's 1000 different classifications. Accordingly, when an image is entered, it passes through a series of layers of dense blocks depending on the design.

Every dense block layer is followed by a transition layer (Convolution and Pooling), which improves the image pixels while reducing the image size and pushes the improved version of the image to the following layers. The model identifies the images after going through a few levels. The summary of Densenet169 build is illustrated in figure 5.

C. HYBRID CNN AND RNN MODEL

Jain et al [21] proposed in 2018 hybrid CNN-RNN model for Facial Emotion Recognition (FER). In this paper, we adopt the method for Alzheimer disease prediction. The CNN model utilized for feature extraction had all of its parameters fixed, and the regression layer was removed. To process the image, 200-dimensional vectors will be retrieved from the fully linked layers when the image is sent to the network. P frames are used from the past for the time t (i.e. [t P, t]). The CNN is then asked to pass each frame from time t P to t and fully extract P vectors from each image. The RNN model's nodes pass through each vector.

V. RESULTS AND DISCUSSION

Proper cognitive stimulation, along with an early diagnosis of Alzheimer's disease, can lessen the effects on elderly persons and their families.

Artificial intelligence is a study used for the early detection of conditions in the very first stage and is used to diagnose this disease. The images are first normalized using Scaling. Then different data augmentation methods are performed to augment the training dataset, namely: vertical flip, random rotation, and horizontal flip.

- Random rotation: The method rotates the image at random between -90 and +90 degrees.
- Horizontal Flip: A horizontal flip produces an image that is mirror-image of the original along the vertical axis.
- Vertical Flip: Vertical Flip is a method that flips the original image horizontally to produce the mirror image.

By creating new but distinct versions of the original images, these strategies aim to increase the amount of training data for the model training phase. These images are used to build an AD detection model based on CNN, Densenet169, AND hybrid CNN_RNN algorithms. At the model evaluation step, these models are compared based on the accuracy and use of the best model to detect AD. The results based on the CNN algorithm are illustrated in figure 5. Figure 6 demonstrates the result of Densenet169, whereas the results of the Hybrid CNN-RNN algorithm are in figure 7. The results of Alzheimer's disease prediction based on CNN, Densenet169, and the Hybrid CNN-RNN model are illustrated in Figure 8. A performance comparison between the proposed and previous work is illustrated in Table 2.

Model: "sequential_1"

Layer (type)	Output Shape	Param #
rescaling_1 (Rescaling)	(None, 128, 128, 3)	0
conv2d_3 (Conv2D)	(None, 128, 128, 16)	448
max_pooling2d_3 (MaxPooling2D)	(None, 64, 64, 16)	0
conv2d_4 (Conv2D)	(None, 64, 64, 32)	4640
max_pooling2d_4 (MaxPooling2D)	(None, 32, 32, 32)	0
dropout_2 (Dropout)	(None, 32, 32, 32)	0
conv2d_5 (Conv2D)	(None, 32, 32, 64)	18496
max_pooling2d_5 (MaxPooling2D)	(None, 16, 16, 64)	0
dropout_3 (Dropout)	(None, 16, 16, 64)	0
flatten_1 (Flatten)	(None, 16384)	0
dense_2 (Dense)	(None, 128)	2097280
dense_3 (Dense)	(None, 4)	516

Total params: 2,121,380
Trainable params: 2,121,380
Non-trainable params: 0

Figure 4. Summary of CNN model

Model: "sequential"

Layer (type)	Output Shape	Param #
densenet169 (Functional)	(None, 7, 7, 1664)	12642880
dropout (Dropout)	(None, 7, 7, 1664)	0
flatten (Flatten)	(None, 81536)	0
batch_normalization (BatchNormalization)	(None, 81536)	326144
dense (Dense)	(None, 2048)	166987776
batch_normalization_1 (BatchNormalization)	(None, 2048)	8192
activation (Activation)	(None, 2048)	0
dropout_1 (Dropout)	(None, 2048)	0
dense_1 (Dense)	(None, 1024)	2098176
batch_normalization_2 (BatchNormalization)	(None, 1024)	4096
activation_1 (Activation)	(None, 1024)	0
dropout_2 (Dropout)	(None, 1024)	0
dense_2 (Dense)	(None, 4)	4100

Total params: 182,071,364
Trainable params: 169,259,268
Non-trainable params: 12,812,096

Figure 5. Summary of Densenet169 model

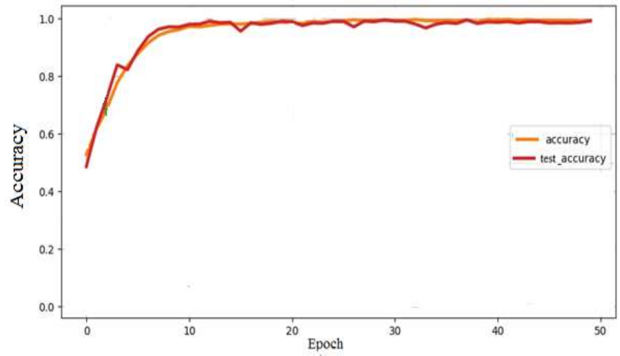

Figure 6. Results of CNN algorithm

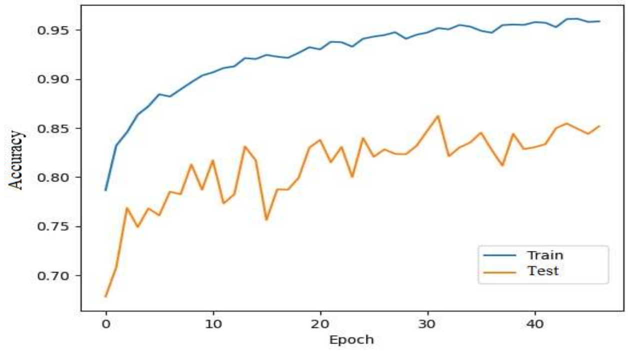

Figure 7. Results of Densenet169 with transfer learning algorithm

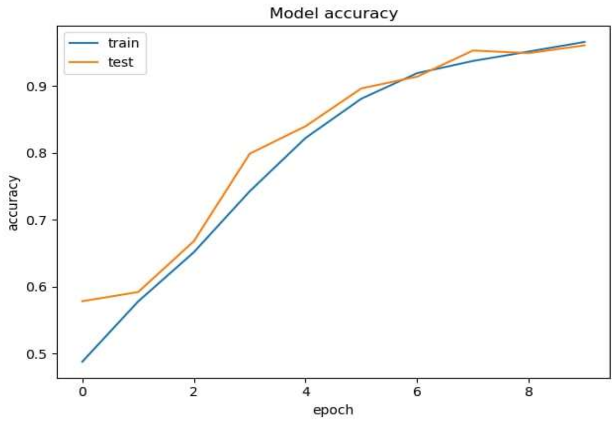

Figure 8. Results of Hybrid CNN-RNN algorithm

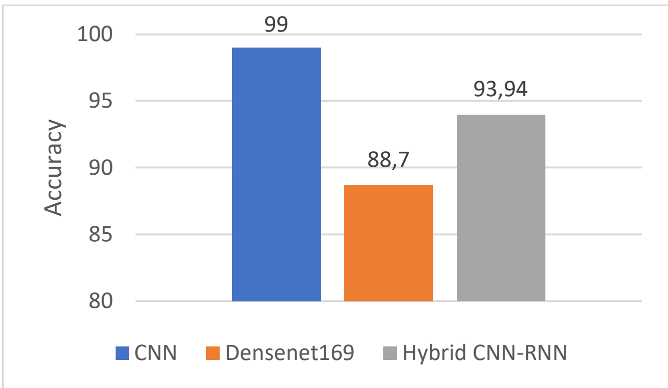

Figure 9. Results of MRI dataset

Table 2. Performance Comparison with Related Work

Reference	Method	Dataset	Accuracy (%)
[9]	LASSO+ multivariate logistic regression	Hospital of Xinjiang Uygur region	80%
[10]	Multimodal RNN	MRI	81%
[11]	Combined DNN and CNN	MRI+fMRI	92.5%
[12]	3D CNN	MRI+PET	AD:NC 93.21:94.5
[13]	Ensemble learning classifier	MRI	98.59%
[14]	3D CNN	Multimodal MRI	98.21% 91% 85.9%
Proposed Method	CNN	MRI	99%
	Densenet169		88.7%
	Hybrid CNN and RNN		93.94%

VI. CONCLUSIONS

Here, we presented a multi-modal deep learning strategy to research Alzheimer's disease prediction. This work successfully created and implemented an automated machine learning tool for the diagnosis of Alzheimer's disease. The tool used a deep learning algorithm. We also examined the performance levels of CNN, Densenet169 with transfer learning, and the Hybrid CNN-RNN model. Deep learning shows a high accuracy level of about 88-99% in AD prediction. Data augmentation technique enhanced the model performance. The average achieved accuracy rate is 99%, 88.7%, and 93.94% when considering CNN, Dense169 with transfer learning, and hybrid CNN-RNN, respectively, with the model proposed for AD classification.

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Wasan Ahmed Ali, M.S.C computer science, university of Diyala, College of Science, Department of computer science, Iraq.