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| RESEARCH ARTICLE

Improved Neural Network-Based System for Early and Accurate Diagnosis of Alzheimer Disease

Spogmay Yousafzai[1], Gul Zaman Khan[2] ✉ Sajad Ulhaq[3], Areebah[4] and Muhammad Rabbi Butt[5]
[12]Department of Computer Software Engineering UET Mardan, Pakistan
[3]Department of Computer Science Ghazi Umara Khan Degree Collage Samar Bagh, Pakistan
[45]School of Computer Science and Technology NCEPU, Beijing, China
Corresponding Author: Gul Zaman Khan, **E-mail**: gulzamankhan726@gmail.com

| ABSTRACT
Alzheimer's disorder is a neurological condition that develops over time and mainly impacts cognitive processes like memory, thought, and behavior. It is one of the most typical reasons for dementia, a syndrome marked by a loss of cognitive ability that interferes with individual daily activities. Recent techniques for diagnosing Alzheimer's illness frequently combine positron emission tomography (PET) scans with magnetic resonance imaging (MRI), which can identify mutations in the brain caused by the illness, such as the buildup of beta-amyloid plaques and tau tangles. Furthermore, analysis of blood samples and cerebrospinal fluid is also a widely used method for the diagnosis of Alzheimer’s disease. Machine learning and deep learning-based techniques play a vital role in examining complex structures in brain images and other data, contributing to the timely and precise identification of Alzheimer's disease. Artificial intelligence-based techniques can help prompt detection and treatment, leading to more efficient care for Alzheimer's disease. This study uses convolutional neural networks (CNN) with MRI-based datasets for early and accurate diagnosis of Alzheimer’s disease. The proposed approach has shown excellent results in AD diagnosis.

| KEYWORDS

Alzheimer disease, intelligent system, classification, Image processing, expert systems

| ARTICLE INFORMATION

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1. Introduction
Alzheimer's disease (AD) is a chronic brain disorder characterized by diminished memory and cognitive impairment caused by the death of brain cells. It is the most frequent form of dementia and has a terrible effect on people's social and personal lives. Alzheimer's illness is a gradual and irreversible neurological condition that disrupts mental abilities and behavior. It is the leading cause of dementia in elderly individuals, responsible for up to 80% of all dementia cases. Alzheimer’s illness has numerous effects on the brain. It results in the accumulation of two aberrant proteins known as amyloid plaques and tau tangles, which harm and destroy brain cells. The human brain shrinks when nerve cells die, and interaction between various parts of the brain is disturbed. This causes signs of the illness, such as loss of memory, disorientation, difficulties with speaking, and changes in behavior and state of mind. Alzheimer's disease typically begins slowly and grows over time. It is classified into three categories: mild, medium, and severe. Individuals with Alzheimer's illness may have trouble recalling recent incidents or recognizing the identities of familiar people in the early stages, but they can still conduct routine tasks independently. In the later phases, an individual may require assistance with routine tasks, including eating, dressing, and showering. Alzheimer's illness can cause a variety of neurological, physical, and emotional symptoms, as well as a higher risk of death in certain situations. People suffering from Alzheimer's disease are more vulnerable to infections along with additional health issues, including pneumonia and infections of the prostate, which can be fatal. According to the most recent statistics, approximately 46.8 million individuals are now suffering from dementia, and

forty-four million of them have AD disease. This population is expected to rise to 131.5 million by 2050 [Dementia 2023]. Mild cognitive impairment, which accounts for 10% of cases of AD, is a phase that occurs between cognitively normal (CN) and dementia [Nguyen 2022]. A total of 84,767 deaths were caused by Alzheimer's disease in 2013. The mortality rate of cardiovascular disease and stroke decreased, while the rate of Alzheimer's increased by 71% between 2000 and 2013 [Qu et al 2023]. Globally, the average lifespan of people has grown due to advancements in health care and diagnosis. However, there is currently a lack of treatment for Alzheimer's disease.

Traditional methods used for the diagnosis of AD include combining medical history, cognitive tests, and physical examination. During medical treatment, the physician inquires about the patient's indications, health record, and history of Alzheimer's disease. The physical examination includes a physical checkup, evaluating brain function, and checking out other medical conditions. Cognitive tests, including the Mini-Mental State Examination (MMSE), investigate memory, focus, and the ability to speak. The traditional methods used for the diagnosis of AD are costly and have unsatisfactory results. Furthermore, these traditional methods require medical expertise, and due to human involvement, there are more chances of inaccurate results. It is crucial to diagnose AD at early stages and accurately to prevent individuals from further loss. The drawbacks of conventional diagnostic techniques draw attention to the need for continual study and the creation of more precise and minimally invasive methods for diagnosis.

Machine learning (ML) and deep learning (DL) techniques have shown remarkable achievements in the diagnosis of various diseases. ML and DL models process large-scale data and have pattern recognition capabilities. These methods can analyze brain image tests like MRIs and PET images to find small variations that might be signs of Alzheimer's disease, enabling early diagnosis and treatment. Additionally, machine learning (ML) methods can predict the possibility of obtaining AD, detect high-risk individuals, and start preventive measures by combining patient data, including medical records, behavioral variables, and genetic details. Furthermore, DL algorithms are able to examine written and spoken patterns, revealing early indications of mental decline and loss of language. This method has the ability to enhance AD detection and treatment at an early stage.

The proposed study uses a CNN-based approach with MRI datasets to diagnose AD at an early stage and efficiently. Furthermore, the proposed study uses some preprocessing and feature selection techniques to standardize the dataset. The key contributions of the proposed study are as follows:

- To develop a smart healthcare system for the early and accurate diagnosis of Alzheimer disease.
- To improve the existing methods and suggest new methods for Alzheimer disease diagnosis.

The rest of the study is organized as follows: Section 2 discusses previous research studies for AD diagnosis; Section 3 depicts material and methods; the results and discussion are discussed in Section 4; and Section 5 describes the conclusion and future work.

2. Literature Review

Machine learning (ML) and deep learning (DL) approaches are now increasingly used in the classification of Alzheimer's disease. Its ability to continuously enhance prediction accuracy by learning the most useful aspects of its environment is a major factor in its widespread use. The following section addresses a number of the most recent, cutting-edge studies for AD classification.

References	Model used	Contribution	Dataset used	Accuracy	Limitations
Dong Nguyen et al.[2]	3D-ResNet, XGBoost	Diagnosis	ADNI MRI dataset	96%	• Used small dataset
ZONGSHUAI QU et al.[3]	UNB-GCN	Diagnosis	ADNI MRI dataset	93.90%	• Used small dataset. • Accuracy can be improved.
Rahmeh Ibrahim et al.[4]	PSO-CNN	Detection	ADNI, Kaggle & BT MRI dataset	98%	• High computation time

F M JAVED MEHEDI SHAMRAT et al.[5]	VGG16, MobileNetV2, AlexNet, ResNet50, InceptionV3, AlzeimerNet.	Classification	ADNI MRI dataset	98.68%	• Used small dataset • High computation time
Waleed Salehi et al.[6]	LSTM	Classification	Kaggle dataset	98.62%	• High computation time
CHAHD M. CHABIB et al.[7]	CNN	Detection	Kaggle dataset	98.62%	• Used small dataset
ANDREAS MILTIADOUS et al.[8]	DICE-net	Detection	AHEPA University Hospital Dataset	83.28%	• Accuracy can be improved
Naveen Sundar et al.[9]	DC-GC-ANN, KNN, DT	Prediction	PPI dataset	96%	• Accuracy can be improved
Ruhul Amin Hazarika et al.[10]	DNN- VGG19	Classification	ADNI MRI dataset	98.08%	• Used small dataset
Sengul Dogan et al.[11]	KNN	Detection	Data Share dataset	92.01%	• High computation time
M. Rajesh Khanna [12]	DCNN, MobileNetV2 and LSTM	Classification	ADNI MRI dataset	90.72	• Used small dataset. • Accuracy can be improved.
Rajarshi SinhaRoy et al.[13]	CNN, DCGANs, and SRGANs	Detection	ADNI MRI dataset	99.7%	• Used small dataset. • High computation time
Peihao Fan et al.[14]	T-LSTM, RETAIN, LR	Detection	UPMCEMR dataset	93.5%	• Accuracy can be improved.
Marilia Lopes et al.[15]	CNN	Classification	NSERC dataset	89.0%	• Used small dataset • Accuracy can be improved.
Afreen Khan et al. [16]	RF, ET, DT, NuSVC, LRCcv, AdaB, GB, GNB, RidgeClasifierCV, KNeighbors.	Classification	OASIS dataset	87%	• Used small dataset. • Accuracy can be improved.
Hadeer A. Helaly et al.[17]	2D-M^{2}IC, 3DM^{2}IC, VGG19	Detection	ADNI MRI dataset	97%	• Used small dataset. • Accuracy can be improved.
Michele Alessandrini et al.[18]	RNN	Classification	Medical diagnosis hospital dataset	97.9%	• High computation time • Accuracy can be improved.

Some approaches have achieved high accuracy, but their time complexity is high, and they utilize a small dataset, while others have average time complexity and utilize a large dataset, but their accuracy is not satisfactory. To tackle the challenges mentioned in Table 1, a lot of research work is needed in AD diagnosis.

3. Proposed methodology

The proposed methodology is divided into two phases: the initial phase involves the collection of data, data preparation, and feature extraction. The second phase consists of machine learning classifiers. Figure 1 provides a detailed explanation of the suggested approach, and the following subsections give brief details of each phase.

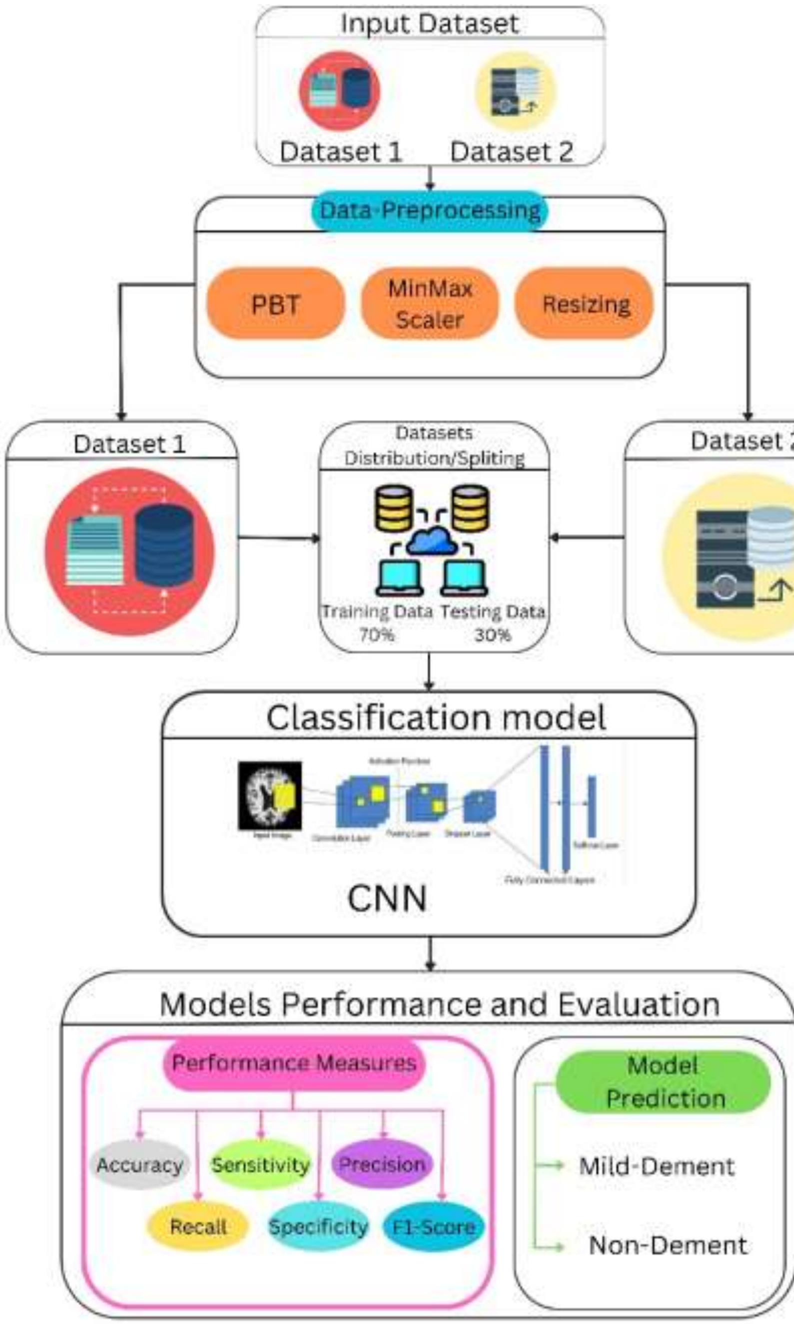

Figure 1. Shows the proposed system methodology

3.1 Dataset collection
The proposed study uses publicly available MRI datasets, which are collected from the Kaggle database. Kaggle dataset 1 consists of 6400 images with two different classes, including demented and non-demented, while dataset 2 consists of mild and non-mild. The proposed dataset samples are collected from people in the age range of 20–88 years. Dataset 1 images are 256 x 256 in size, and dataset 2 images are 264 x 264 in size. We reduced the image to 224 x 224 according to our proposed model requirements.

Table 2 shows the summary of the both datasets.

Dataset	No of instances	Classes	Dataset source
Dataset 1	Total: 6400	Demented	Kaggle online repository.
	Demented: 3200	Non-demented	
	Non demented: 3200		
Dataset 2	Total: 1852	Mild Non-Mild	Kaggle online repository.
	Mild:896		
	Non Mild:956		

3.2 Pre-processing
Preprocessing plays a vital role in machine learning and deep learning-based research [Zaman et al. 2023, Sajad et al. 2023, Badshah et al. 2023, Gul et al. 2023, Zaman et al. 2023, Bashir et al. 2023]. The dataset collected may include low brightness and size issues. The provided approach requires medical image preprocessing for testing and training. Visual device brightness reduces variance, degrading MRI images during development. Enhancing image techniques include linear contrast stretching, which provides increased pixel arrangement across a wide range of intensities to improve MRI scans. The image was noisy during acquisition due to nonlinear light intensity. To overcome these challenges, pixel brightness techniques are first applied to improve image quality. Secondly, the MinMax scaler is applied to scale and transform the features of the image to a specific range. After removing noise, the data augmentation technique is applied. Finally, we divide the proposed dataset into 70 and 30 for training and testing purposes, respectively.

3.3 Classification model
The proposed CNN classification model has several layers that are used to gradually extract features and generate predictions. The first layer, a 2D convolution layer having 32 filters along with a 2x2 kernel size, focuses on feature extraction while maintaining spatial dimensions using ReLU activation and "same" padding. The feature maps are then down sampled using a maxpooling layer with a pool size of 2x2, and overfitting is avoided by using a dropout layer with a rate of 0.2. Convolutional, max-pooling, and dropout layers are used three times, doubling the number of feature maps each time. The feature maps are then transformed into a 1D vector by a flattening layer after this process. A dense layer with 512 neurons with ReLU activation is next connected to the flattened output, followed by a dropout layer with a rate of 0.4. A dense layer with a pair of neurons and a softmax activation function, ideal for binary identification applications, completes the model. The final layer, which can anticipate one of two events, generates class probabilities for the two potential classes. The proposed CNN model architecture is shown in Figure 2.

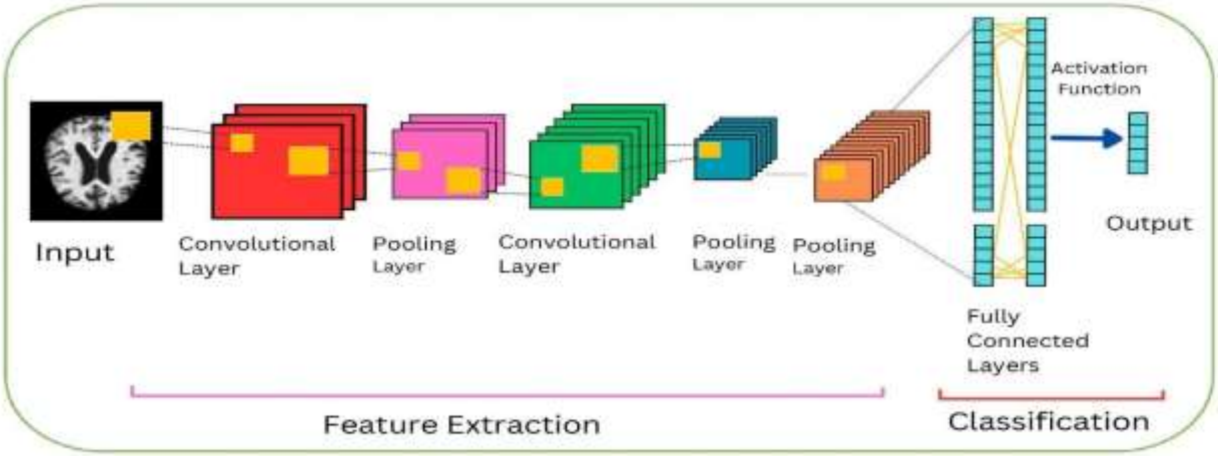

Figure 2. Proposed CNN model architecture

3.4 Performance evaluation matrices

To evaluate the measurements of the proposed CNN model, this study uses confusion matrices, accuracy, precision, F1-score, recall, and ROC. A confusion matrix is an uncomplicated structure that is used in machine learning to measure the achievement of classification techniques. It presents a tabular assessment of predicted vs. actual class labels for a given collection of data, enabling a simple assessment of the model's ability to appropriately categorize situations into different classes. The confusion matrix is separated into four multiple categories, such as (TPs) for true false, (FPs) for false positives, (FNs) for false negatives, and (TNs) for true negatives, as illustrated in Figure 3.

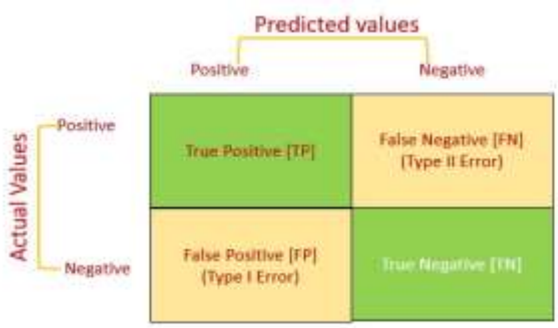

Figure 3 shows the confusion matrix sample.

Also, the outcomes of the proposed system are defined by a confusion matrix. The following metrics are calculated from the CM:

Accuracy can be defined as the percentage of successful predictions to total predictions, i.e., a ratio of properly categorized cases to total occurrences, and it may be expressed as:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP}+ \text{FN}+ \text{FP}+ \text{TN}} \qquad (1)$$

Therefore, the weighted median of recall and accuracy is used to produce the F1-score.

$$\text{F1} - \text{Score} = 2 * \frac{\text{precesion} * \text{recall}}{\text{precision} + \text{recall}}$$

(2)

Additionally, it is useful for unbalanced data. Precision measures the model's ability to accurately predict the positive classification, i.e.,

Where recall is the amount of true positive occurrences for all true positive and false negative events, i.e.,

$$\text{Precision} = \frac{TP}{TP + FP} \quad (3)$$

$$\text{Recall:} = \frac{TP}{TP + FN} \quad (4)$$

The ROC curve is a probability curve that represents the relationship between the false positive rate (1-specificity) and the actual positive rate (sensitivity). It aids in determining a threshold level that strikes a compromise between both specificity and sensitivity.

4. Results and Discussion

In this section of the study, the experimental outcomes of the proposed classifiers are presented. Firstly, we discuss the experimental outcomes of the proposed CNN model with dataset 1. Secondly, we discuss the outcomes with dataset 2. Lastly, we compared the experimental outcomes with dataset 1, dataset 2 and also the suggested approach to the previous studies. The two datasets used in the proposed experiment are divided into 70 and 30 for training and testing purposes. Furthermore, various evaluation metrics are used to measure the performance of the proposed classifier, as shown in Table 2.

Table 2 shows the performance of the proposed model with both datasets

Model used	Dataset	Training accuracy	Testing accuracy	Precision	Recall	F1-score
CNN	Dataset 1	99.8%	99.3%	99	99	0.99
	Dataset 2	100%	100%	100%	100%	1.00

As shown in Table 2, the proposed CNN model achieved an accuracy of 99.3%, precision of 99%, recall of 99%, and F1-score of 0.99 with dataset 1. Similarly, the model achieved accuracy of 100%, precision of 100%, recall of 100%, and an F1-score of 1.00 with dataset 2. The proposed CNN model performance was best with dataset 2 compared to dataset 1. Figure 4 shows the performance of the proposed CNN model.

Figure 4. shows the performance evaluation of the proposed CNN model.

Confusion metrics are used to show the summary of predictions made by the classifier. It shows how many predictions are correct and incorrect per class. The confusion metrics of the proposed classifier utilizing dataset 1 are shown in Figure 5(a), while the confusion metrics with dataset 2 are shown in Figure 5(b).

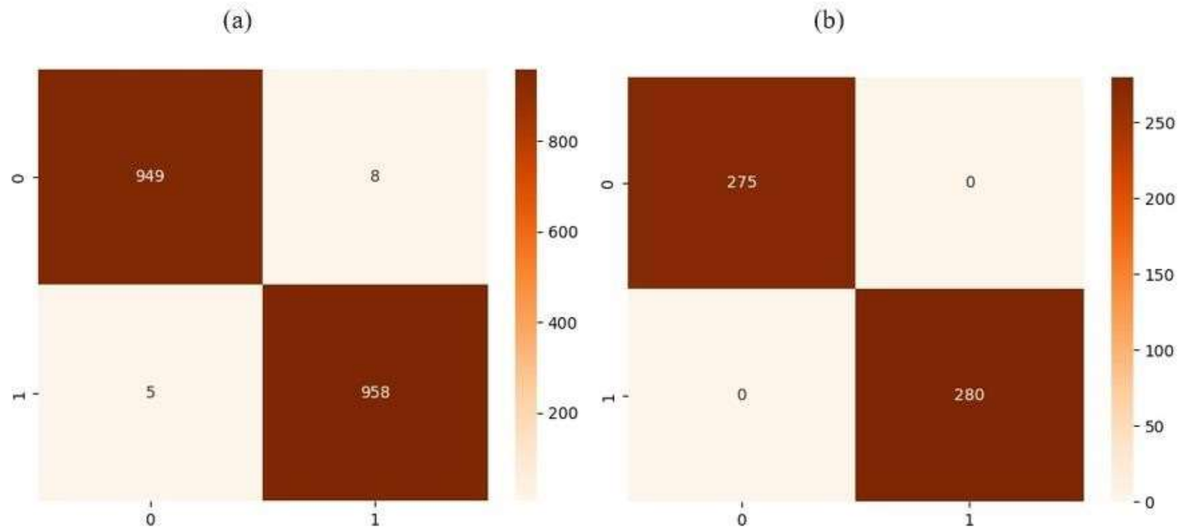

Figure 5 (a) shows the confusion metrics of CNN with dataset 1, and Figure 5 (b) shows the confusion metrics utilized with dataset 2.

Utilizing dataset 1, out of 957 records, the CNN model predicted 949 records correctly and 9 records incorrectly; likewise, out of 963 records, the proposed CNN model predicted 958 records correctly and 5 records incorrectly. Similarly, utilizing dataset 2, the proposed model predicted all records correctly and was 100% accurate. Training and testing accuracy of CNN with dataset 1 is shown in Figure 6(a), while Figure 6(b) shows training and testing accuracy with dataset 2.

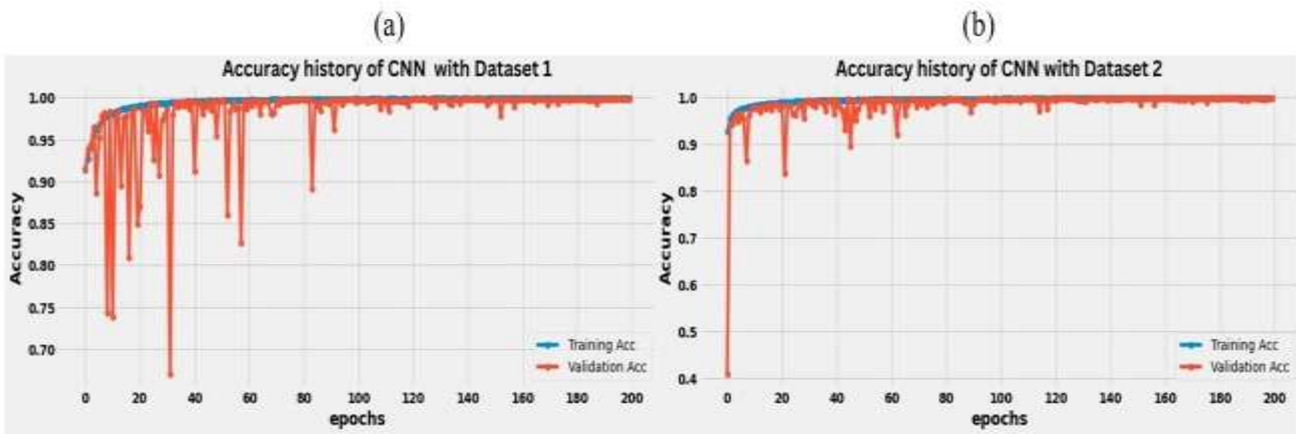

Figure 6(a) shows the accuracy history utilized in dataset 1, and Figure 6(b) shows the accuracy history utilized in dataset 2.

Figure 6(a) shows that the training accuracy was higher than the validation accuracy, so the proposed model was the best fit. Similarly, Figure 6b shows that in the beginning, training accuracy was high, and validation accuracy gradually increased in later epochs.

5. Conclusion

In this work, an innovative deep learning algorithm was developed to successfully predict Alzheimer's illness. The method made use of two different datasets that were obtained from the Kaggle online repository and carefully preprocessed. These processes included methods including Min-Max scaling for the best data normalization, resizing to improve image quality, and Pixel Brightness Transformation (PBT) to capture pertinent image features. The constructed model demonstrated a notable improvement over earlier strategies, producing the highest accuracy thus far compared to earlier techniques. In the future, we will apply some hybrid models for multi-class Alzheimer disease classification. Also, we will work on EEG signal-based data for early detection of Alzheimer disease.

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