BIG DATA MINING AND ANALYTICS
ISSN 2096-0654 09/10 pp504–512
Volume 6, Number 4, December 2023
DOI: 10.26599/BDMA.2022.9020049

Diagnosis and Detection of Alzheimer's Disease Using Learning Algorithm

Gargi Pant Shukla, Santosh Kumar, Saroj Kumar Pandey, Rohit Agarwal, Neeraj Varshney, and Ankit Kumar*

Abstract: In Computer-Aided Detection (CAD) brain disease classification is a vital issue. Alzheimer's Disease (AD) and brain tumors are the primary reasons of death. The studies of these diseases are carried out by Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), and Computed Tomography (CT) scans which require expertise to understand the modality. The disease is the most prevalent in the elderly and can be fatal in its later stages. The result can be determined by calculating the mini-mental state exam score, following which the MRI scan of the brain is successful. Apart from that, various classification algorithms, such as machine learning and deep learning, are useful for diagnosing MRI scans. However, they do have some limitations in terms of accuracy. This paper proposes some insightful pre-processing methods that significantly improve the classification performance of these MRI images. Additionally, it reduced the time it took to train the model of various pre-existing learning algorithms. A dataset was obtained from Alzheimer's Disease Neurological Initiative (ADNI) and converted from a 4D format to a 2D format. Selective clipping, grayscale image conversion, and histogram equalization techniques were used to pre-process the images. After pre-processing, we proposed three learning algorithms for AD classification, that is random forest, XGBoost, and Convolution Neural Networks (CNN). Results are computed on dataset and show that it outperformed with exiting work in terms of accuracy is 97.57% and sensitivity is 97.60%.

Key words: alzheimer's disease; deep learning; random forest; XGBoost

1 Introduction

Alzheimer's Disease (AD) is a progressive neural disease that causes memory loss over time. Alzheimer's disease is the most common cause of dementia[1]. The disease starts with mental decline and progresses to a neurodegenerative form of dementia. To diagnose Alzheimer's, a patient's history, Mini-Mental State Examination (MMSE) score, and neurobiological exams are all required. Additionally, structural Magnetic Resonance Imaging (s-MRI) and resting-state Magnetic Resource Imaging (rs-MRI) are critical in the diagnosis of Alzheimer's disease[2]. Individuals lie down on the MRI table and refrain from performing other tasks while the resting-state functional Magnetic Resource Imaging (rs-fMRI) is being scanned to avoid interfering with other brain functions[3]. Alzheimer's disease causes the hippocampus and cerebral cortex of the brain to shrink.

The stage determines the severity of the disease at the time. In severe cases, the ventricles can enlarge, as seen

• Gargi Pant Shukla is with the Department of Management, Doon Business School, Dehradun 248001, India. E-mail: gargipant87@gmail.com.
• Santosh Kumar is with the Jaipuria Institute of Management, Jaipur 302033, India. E-mail: talksant@gmail.com.
• Saroj Kumar Pandey, Rohit Agarwal, Neeraj Varshney, and Ankit Kumar are with the Department of Computer Engineering and Apllications, GLA University, Mathura 281406, India. E-mail: saroj.pandey@gla.ac.in; rohit.agrwal@gla.ac.in; neeraj.varshney@gla.ac.in; iiita.ankit@gmail.com.
* To whom correspondence should be addressed.
Manuscript received: 2022-07-28; revised: 2022-11-21; accepted: 2022-11-28

on MRI scans. These, in turn, have an impact on an individual's thinking capacity as well as judgment and planning abilities[4].

There is currently no cure for Alzheimer's disease. Nonetheless, early treatment following an immediate diagnosis can significantly reduce the severity of symptoms, providing some relief to the patient and reducing his/her suffering. When a diagnosis is made early on, treatments are highly advantageous and effective. An early diagnosis can reduce memory loss for a significant period of time[5].

After a successful diagnosis of AD, one can find the following most common kinds of anomalies in the brain scans of the patient.

(1) A thick layer consists of protein sediment on the boundaries of the nerve cells.

(2) Damaged nerve fibers tangled on the inside nerve cells.

In some cases, the information has been used to diagnose Alzheimer's disease[6]. The diagnosis of AD requires an accurate medical evaluation, detailed and exhaustive patient records, MMSE report, and a number of other neurobiological and physical examinations[7]. In addition to structural s-MRI and rs-fMRI, imaging is one of the most prevalent techniques for analyzing and visualizing regular changes in the brain[8].

Advanced learning algorithms, such as DL, can effectively classify AD, thereby aiding numerous scientists and medical professionals in diagnosing the disease. These algorithms are also useful for making accurate and timely Alzheimer's diagnoses[9]. The paper's primary contribution and the remainder of the paper's flow. To conduct our experiments, we downloaded the dataset from the Alzheimer's Disease Neurological Initiative (ADNI) website. Priority was given to preprocessing the dataset prior to feeding it to a classification model. Initially, we utilized existing libraries to convert the images into 2D images (Dicom). Following this, we eliminated the images that did not contribute significantly to the dataset's informational value. By converting these images from RGB to grayscale format, we were able to improve their quality while simultaneously reducing the dataset's complexity. Moreover, we utilized Generative Adversarial Networks (GAN) to produce identical and synthetic images.

2 Literature Review

In this section, we conducted a thorough literature review on Alzheimer's disease by employing machine learning techniques.

In Ref. [10], a method was developed in which learning algorithms contribute to the determination of the patient's behavior over time. The concept is to use Estimote Bluetooth beacons to locate a patient's home. It is a highly dependable method that can pinpoint the patient's location with an accuracy of over 90%. Sorensen, Lauge, and coworkers investigated whether hippocampal texture could be a useful MRI-based characteristic for early Alzheimer's disease diagnosis. 83% of their observations were accurate. In this study, the feature was found to have significantly better classification between stable Mild Cognitive Impairments (MCI) and MCI-to-AD converters.

In addition, the authors of Ref. [11] utilized deep learning, specifically stacked auto-encoders and the softmax activation function in the output layer. This minor change resolved the bottleneck issue. In comparison to previous classification techniques, their method requires fewer training data and minimal information to perform multi-class classification. They classified all diagnosis groups with approximately 87.70% accuracy. A significant finding of their research is that combining multiple features can improve classification performance.

In addition, the authors of Ref. [12] proposed a categorization structure that exploits the complementarity of the different input databases. Then, a nonlinear graph mixture process is applied to a variety of aggregate features derived from distinct modalities. After combining these graphs, the Area Under Curve (AUC) of the r-o attribute was found to be 98.1% between AD and NC (standard control) images and 82.40% between NC and MCI images. In the overall classifications, they achieved an AUC of 77.90%.

Using various techniques, the authors of Ref. [13] extracted characteristics from MRI (diffused) images. They utilized pixel-wise distribution calculations that were framed using the Region-Based Spatial Statistics (RBSS). Using Independent Component Analysis (ICA), they clustered the pixel-wise distribution and discovered the combination of these features.

In this study we have used an existing approach on the ADNI dataset that optimizes the computational cost over other existing prediction methods. Other existing work has higher computational cost in terms of time complexity as the number of parameters increases the time complexity of the model. Here we have used three combination methods which do three different tasks.

First, convert gray scale image from 3D to 2D, then clip the images to reduce the size of image and cut unnecessary borders from image, and finally[14] use PCA to extract optimum features from datasets.

Mirzaei and Adeli[14] proposed a deep learning based convolutional neural network for Alzheimer's disease diagnosis which indicates that there is no single best approach for Alzheimer's disease classification. They have used transfer learning through which they overcame the limitations of the availability of large numbers of medical images.

Table 1 summarizes some of the benchmark work done in detecting and diagnosing Alzheimer's disease using learning algorithms in this report. Comparative anlaysis of exiting work is done in Table 1.

3 Material and Method

We have acquired the dataset from the ADNI website (Reference) for carrying out the experiments. Given below is a flowchart detailing the proposed models. Please refer to Fig. 1.

3.1 Dataset description

The database is taken from the Alzheimer's Disease Neurological Initiative (ADNI) to perform the experiments. The dataset consists of a total of 3692 images. The images are categorized into two categories, of which 1917 images belong to the class AD (which stands for Alzheimer's disease), and the rest of 1775 images belong to the average person class denoted by NL.

3.2 Pre-processing methods

We have pre-processed the data to be used in the proposed method by a different method.

3.2.1 Image conversion

Image conversion converts a given input image into the desired format as an output image. Here, we are given an array of images converted into 2D images. This conversion process can be described as follows. First, we read the input image[18]. Then for each image we read, we load it into the Viacom library. After that, we store the i-th component of the image in the x vector, the j-th component in the y vector, and the k-th component of the image in the z vector. Then for each of the components in the z vector, we make a separate image file by combining the image from the x and y vectors. Hence, for each component of the z vector, we save the corresponding x and y vectors. In this way, we generate the 2D images.

3.2.2 Parameter reduction and selective clipping

The ADNI dataset we have used for this report consists of several cross-section layers of MRI scans of the brain, which is further divided into two categories: healthy, which is represented by NL, and diseased person, which is represented by AD[17]. We have significantly modified the dataset for this report according to our needs. To generate the maximum efficiency of our model and thus a better output, we have sliced those parts of the dataset which contained the cross-sectional scans of the brain, which were located near the edge of the skull, and hence provided no extra information regarding the orientation of the brain, as shown in Fig. 2.

A brain edge scan is depicted in Fig. 3. The cross-sections at the edge of the skull contain very little information, which hinders our efforts to develop a model[14]. Consequently, we segmented images from both our training and testing datasets. By modulating the intensities of the pixels in the dataset using the histogram equivalence technique, which balances the contrast of the images to improve their quality, additional quality improvements were made to the dataset. Using a technique known as grayscale conversion, we reduced

Table 1 Comparative analysis of exiting literature.

Author and year	Used dataset	Applied procedure	Sensitivity (%)	Specificity (%)	Accuracy (%)
Liu et al.[15] (2022)	ADNI	Modified Vox CNN	–	–	86.3±061
Maqsood et al.[16] (2019)	BRATS	K means clustering, ANN, and SVMs	–	–	90.90
Mirzaei et al.[17] (2016)	Brain-tumor MRI scans (540)	Modified Counter Propagation Neural Network (MCPNN) and Modified Kohonen Neural Network (MKNN)	90.00	96.00	95.00
Mirzaei and Adeli[14] (2022)	HMS database	Variational Mode Decomposition (VMD)	99.43	–	90.68
Mehmood et al.[18] (2021)	ADNI	AlexNet, transfer learning, and CNN	–	–	98.74
Mundt et al.[19] (2000)	ADNI	VGG-16 and PfSeCtl model	–	–	95.73

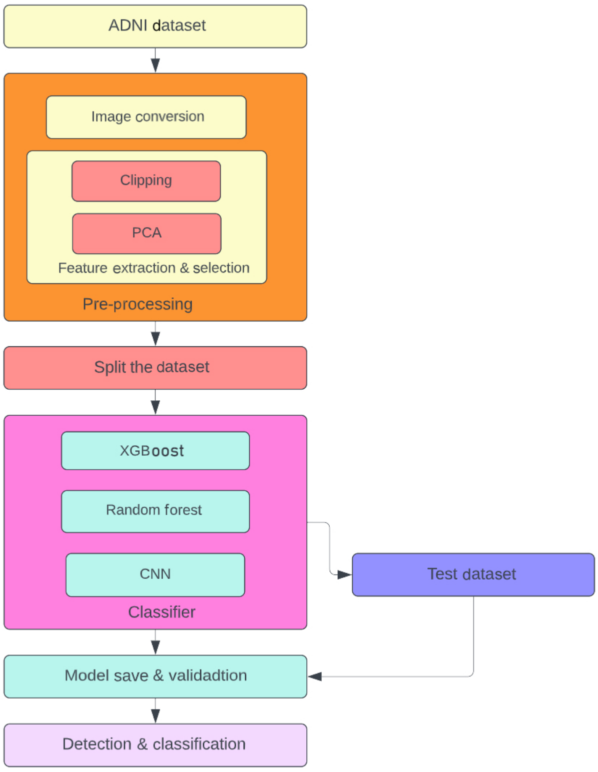


Fig. 1 Flowchart of the methodology of the work.

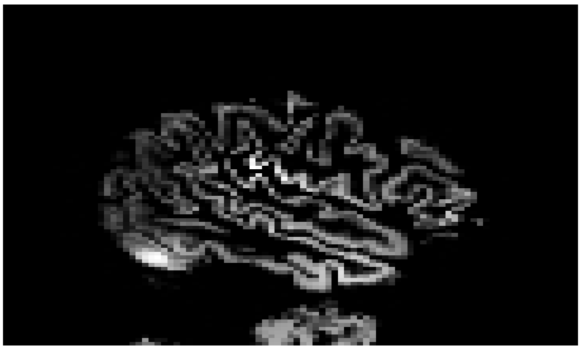


Fig. 2 An image consisting of the scan of the brain near the center of the skull.

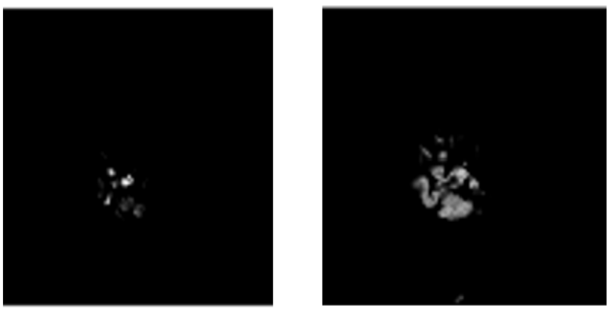


Fig. 3 Images consisting of scans of the brain located at the edge.

the input dataset's parameters even further. The input image was originally in RGB format, but we converted it to grayscale to aid in simplifying the dataset. The reduction of these features will not result in data loss because these scans are already available in grayscale format, and it will have no effect on the images' capacity for learning. Figure 4 depicts a process in which there is no discernible loss of data.

3.2.3 Principal components analysis

The principal component analysis[19] gave a set of points in dimensional space (greater than three), which define as the "best-fitting" line that minimizes the average squared distance from a point to the line. The best-fitting line from directions is perpendicular to the first. To obtain an orthogonal basis where different individual data dimensions are uncorrelated, we can use the Gram-Schmidt process. The discovered basis vectors are referred to as principal components, and the numerous related procedures are referred to as Principal Component Analysis (PCA).

To implement PCA:

(1) First, calculate a matrix that illustrates how all the variables relate to each other.

(2) Then, we can slice this matrix down into two separate components: direction and magnitude.

(3) We can then understand the directions and magnitude of the data and how important these are.

(4) Next, we can convert our original data to align with these important directions.

(5) In doing so, we are reducing the dimensionality of our feature space.

The pre-processed data are then used to train standard classification algorithms, namely random forest algorithm, XGBoost classification, and CNN model.

3.3 Deep learning classifiers

We have used different methods for categorize images in the normal and AD categories. To find the best classifier to produce the best results in the ADNI dataset after performing rigorous pre-processing, we have extensively

Fig. 4 Enhancing images dramatically increases the quality.

used Convolution Neural Networks (CNNs) among these methods. Apart from using CNN, we employed various other classification models, including random forest and XGBosst[20].

Convolution neural network. The convolutional neural networks, or CNNs for short, were designed after drawing inspiration from the brain and its processes. The patterns of the connection between the said neurons in these models replicate that of the organization of the animal visual cortex. The convolutional neural network comprises of following layers:

First layer: The first layer is called the convolutional layer. It is also called the primary layer or the main layer. Its job is to perform filtration from the incoming layer by analyzing a set of given patterns. This layer produces an output layer containing the elements filtered out using those specific conditions. A general representation of this layer is done in the shape of cubical blocks.

Second layer: The second layer is also called the max-pooling layer or simply the pooling layer. It is used to execute the operations, which are done after the convolutional layer. The primary purpose of this layer is to mitigate the size of the input matrix by taking the maximum value of each block. Thus, this layer can be considered as a size reduction layer consisting of small grids iterating over the original input matrix and outputting the maximum value present in each grid[21].

Third layer: This layer is also called the fully connected layer and is the final layer of CNN or the convolutional neural network. It is a traditional fully connected layer that is made by connecting all previous architecture nodes. It significantly diminishes spatial information due to its connectivity and is similar to the common Artificial Neural Networks (ANNs)[22]. The nodes at the end of these layers finally categorize the input data into the output, as shown in Table 2.

Table 2 Model of proposed CNN model.

Layer (type)	Output shape	Parameter
Convolutional layer-1	(None, 107, 89, 32)	320
Convolutional layer-2	(None, 105, 87, 64)	18 496
Max-pooling layer	(None, 52, 43, 64)	0
Dropout-1	(None, 52, 43, 64)	0
Flatten	(None, 143104)	0
Dense layer-1	(None, 128)	18 317 440
Dropout-2	(None, 128)	0
Dense layer-2	(None, 2)	258

Note: Total parameter: 18 336 514; trainable parameter: 18 336 514; non trainable parameter: 0.

3.4 Machine learning classifiers

In this section, we have implemented the different machine learning algorithms on this dataset and analyzed the result with our proposed work.

3.4.1 Random forest

Random forest is yet another learning algorithm supervised in nature and can be used to classify the image dataset[23, 24]. Like a typical forest consisting of trees, we can say that the forest is highly robust if it is highly dense. We can use the same analogy in the case of the random forest algorithm. It forms decision trees on the given input, gets the output from each of them, and finally selects the most voted output. It is a type of ensemble method which outperforms an algorithm with a single decision tree because it reduces over-fitting[25].

3.4.2 XGBoost

It is yet another classification algorithm that is implemented using boosted trees. It is a form of supervised learning algorithm which predicts an output by ensembling the results of the simpler model. The training is done iteratively by appending fresh trees that predict previous trees' errors mixed with previous trees to make the final output[26]. It is known as gradient boosting because it employs gradient descent algorithms to mitigate the loss.

4 Experimental Result

We have used the GPUs on Kaggle to perform our model training. We have varied our epochs to achieve the best possible results. We have used accuracy and sensitivity as the measures to find the correctness of our model. For dividing the dataset[27], we have used the train_test_split library from sklearn. The training consists of 70% of the dataset, and the testing consists of the remaining 30% of the whole dataset.

In Table 3, we have compared classification accuracy by different models before and after applying pre-processing methods. In Table 4, we have compared the training time of the model before and after applying pre-processing techniques. From Table 5, it can be seen that the model training time[28, 29] has significantly decreased after applying the pre-processing to the database. In Table 6, we have compared the existing benchmark results with our results and thus shown that our methods are superior with the work done by some other reputed authors.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{FN} + \text{TN}} \times 100\% \qquad (1)$$

Table 3 Comparing the accuracy obtained before and after applying pre-processing.

Classification algorithm	Accuracy before pre-processing (%)	Accuracy after pre-processing (%)
Random forest	82.80	86.93
XGBoost	90.11	92.85
Proposed CNN model	95.14	97.59

Table 4 Comparing the training time before and after applying pre-processing.

Learning algorithm	Training time before pre-processing (s)	Training time after pre-processing (s)	Percentage of decrease (%)
XGBoost	1436.94	378.64	73.65
Proposed CNN model	126.85	83.73	34
Random forest	21.86	8.66	60.38

Table 5 Performance comparison of learning algorithms using ADNI dataset. (%)

Model	Accuracy	Precision	Specificity	F1-score
CNN model	96.43	98.02	96.35	97.22
XGBoost	92.37	91.75	92.36	92.05
Random forest	85.90	88.45	85.38	87.15

Table 6 Comparative anlaysis of proposed work with exiting work.

Author and year	Methodology	Accuracy (%)
Suk and Shen[30] (2013)	Stack autoencoder based deep learning	95.90
Sarraf et al.[31] (2019)	CNN and LeNet-5	96.84
Zhang et al.[32] (2016)	SVM	93.20
Proposed	RF, XGBoost, and CNN	97.52

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100\% \quad (2)$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \times 100\% \quad (3)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \times 100\% \quad (4)$$

$$\text{F1-score} = 2 \times \frac{P \times \text{Se}}{P + \text{Se}} \times 100\% \quad (5)$$

where TP = True Positive, FN = True Negative, FP = False Positive, TN = True Negative, P is Precision, and Se is Sensitivity.

$$\text{Decrease in computation time} = \frac{\text{TB} - \text{TA}}{\text{TB}} \times 100\% \quad (6)$$

where TB = time taken before pre-processing, TA= time taken after pre-processing.

Performance comparison of algorithms. This section displays the classified results from three prediction models after applying the pre-processing to the dataset. We compared three models[33,34] using accuracy, sensitivity, and specificity, as shown in Fig. 5.

Table 6 represents the comparative anlaysis of proposed work with their proposed method. Figure 6 shows that our proposed work clearly outperformed with exiting methods.

5 Conclusion

This research paper introduces innovative pre-processing methods that provide valuable insights. These pre-processing techniques play a pivotal role in improving the accuracy of classification algorithms. Additionally, the proposed methods contribute to the reduction of training time required for existing learning algorithms, making the diagnostic process more efficient and practical. The study used a dataset obtained from the ADNI, which was transformed from a 4D format to a 2D format to facilitate further analysis. The dataset underwent meticulous pre-processing steps, including

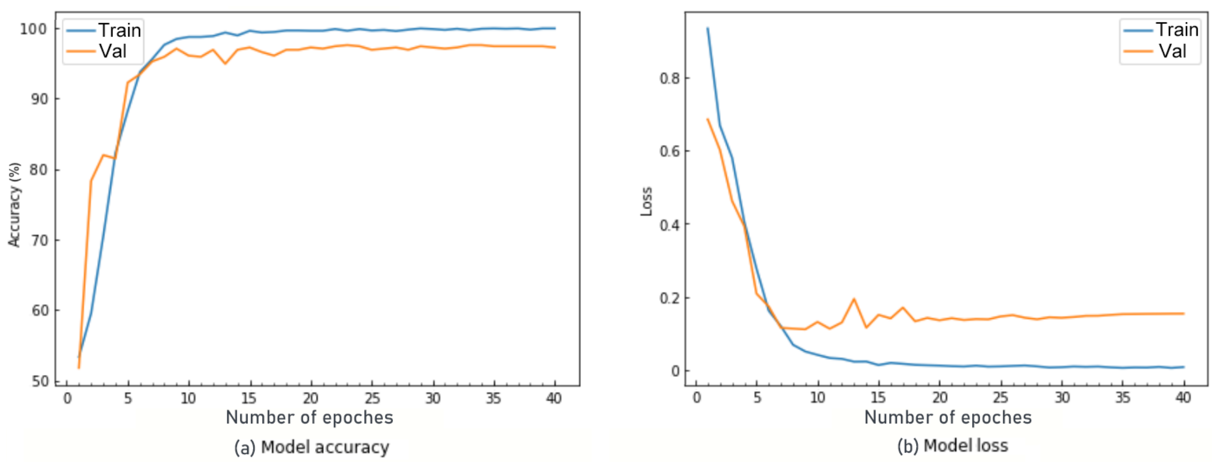
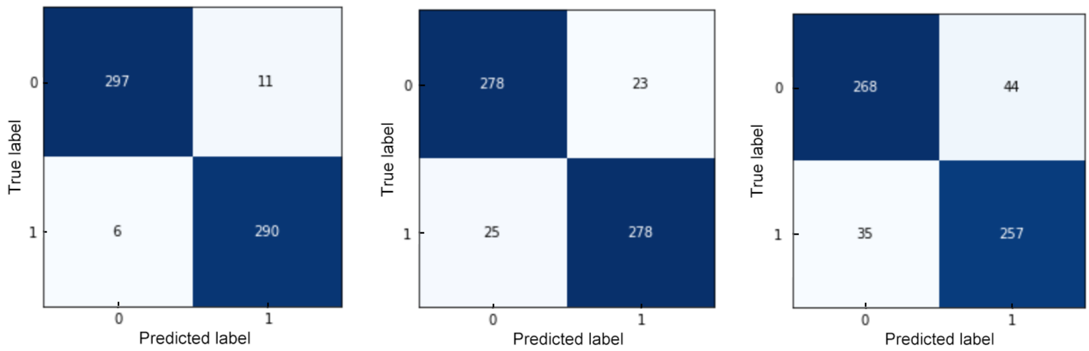


Fig. 5 Accuracy curve and loss curve.



(a) Model (CNN) (b) XGBoost (c) Random forest

Fig. 6 Depiction of confusion matrix on test dataset.

selective clipping, grayscale image conversion, and histogram equalization, which enhance the quality and discriminatory power of the MRI images. In the subsequent stages, three different learning algorithms were proposed for AD classification: random forest, XGBoost, and CNN. These algorithms leverage the pre-processed MRI images to accurately classify and diagnose the presence of AD. The experimental results obtained from the dataset demonstrate the superior performance of the proposed approach compared to existing works in the field. The approach achieved an impressive accuracy rate of 97.57% and a sensitivity of 97.60%, affirming its effectiveness in accurately detecting and diagnosing AD. The findings of this research offer promising prospects for the field of brain disease diagnosis, particularly in terms of leveraging pre-processing techniques to enhance the performance of classification algorithms and reduce training time. The proposed approach holds the potential to significantly contribute to the early and accurate diagnosis of AD and other brain diseases, leading to improved patient care and outcomes.

References

[1] M. R. Ahmed, Y. Zhang, Z. Q. Feng, B. Lo, O. T. Inan, and H. Liao, Neuroimaging and machine learning for dementia diagnosis: Recent advancements and future prospects, *IEEE Reviews in Biomedical Engineering*, vol. 12, pp. 19–33, 2018.

[2] S. T. Ahmed and S. M. Kadhem, Early Alzheimer's disease detection using different techniques based on microarray data: A review, *International Journal of Online and Biomedical Engineering*, vol. 18, no. 4, pp. 106–126, 2022.

[3] M. H. Al-Adhaileh, Diagnosis and classification of Alzheimer's disease by using a convolution neural network algorithm, *Soft Computing*, vol. 26, no. 16, pp. 7751–7762, 2022.

[4] S. Al-Shoukry, T. H. Rassem, and N. M. Makbol, Alzheimer's diseases detection by using deep learning algorithms: A mini-review, *IEEE Access*, vol. 8, pp. 77131–77141, 2020.

[5] G. S. Babu and S. Suresh, Sequential projection-based metacognitive learning in a radial basis function network for classification problems, *IEEE Transactions on Neural Networks and Learning Systems*, vol. 24, no. 2, pp. 194–206, 2013.

[6] R. Baik, Class imbalance learning-driven Alzheimer's detection using hybrid features, *International Journal of Distributed Sensor Networks*, doi: 10.1177/15501477 19826048.

[7] W. H. Bangyal, N. U. Rehman, A. Nawaz, K. Nisar, A. A. A. Ibrahim, R. Shakir, and D. B. Rawat, Constructing domain ontology for alzheimer disease using deep learning based approach, *Electronics*, vol. 11, no. 12, p. 1890, 2022.

[8] B. Bigham, S. A. Zamanpour, H. Zare, and Alzheimer's Disease Neuroimaging Initiative, Features of the superficial white matter as biomarkers for the detection of Alzheimer's disease and mild cognitive impairment: A diffusion tensor imaging study, *Heliyon*, vol. 8, no. 1, p. e08725, 2022.

[9] L. Billeci, A. Badolato, L. Bachi, and A. Tonacci, Machine learning for the classification of Alzheimer's disease and its prodromal stage using brain diffusion tensor imaging data: A systematic review, *Processes*, vol. 8, no. 9, p. 1071, 2020.

[10] A. D. Blackwell, B. J. Sahakian, R. Vesey, J. M. Semple, T. W. Robbins, and J. R. Hodges, Detecting dementia: Novel neuropsychological markers of preclinical Alzheimer's disease, *Dementia and Geriatric Cognitive Disorders*, vol. 17, nos. 1&2, pp. 42–48, 2003.

[11] T. O. Frizzell, M. Glashutter, C. C. Liu, A. Zeng, D. Pan, S. G. Hajra, R. C. N. Arcy, and X. Song, Artificial intelligence in brain MRI analysis of Alzheimer's disease over the past 12 years: A systematic review, *Ageing Research Reviews*, vol. 77, p. 101614, 2022.

[12] H. B. Guo and Y. J. Zhang, Resting state fMRI and improved deep learning algorithm for earlier detection of Alzheimer's disease, *IEEE Access*, vol. 8, pp. 115383–115392, 2020.

[13] J. X. Liu, M. X. Li, Y. L. Luo, S. Yang, W. Li, and Y. F. Bi, Alzheimer's disease detection using depthwise separable convolutional neural networks, *Computer Methods and Programs in Biomedicine*, vol. 203, p. 106032, 2021.

[14] G. Mirzaei and H. Adeli, Machine learning techniques for

diagnosis of Alzheimer disease, mild cognitive disorder, and other types of dementia, *Biomedical Signal Processing and Control*, vol. 72, p. 103293, 2022.

[15] Z. M. Liu, E. J. Paek, S. O. Yoon, D. Casenhiser, W. J. Zhou, and X. P. Zhao, Detecting Alzheimer's disease using natural language processing of referential communication task transcripts, *Journal of Alzheimers Disease*, vol. 86, no. 3, pp. 1385–1398, 2022.

[16] M. Maqsood, F. Nazir, U. Khan, F. Aadil, H. Jamal, I. Mehmood, and O. -Y. Song, Transfer learning assisted classification and detection of Alzheimer's disease stages using 3D MRI scans, *Sensors*, vol. 19, no. 11, p. 2645, 2019.

[17] G. Mirzaei, A. Adeli, and H. Adeli, Imaging and machine learning techniques for diagnosis of Alzheimer's disease, *Reviews in the Neurosciences*, vol. 27, no. 8, pp. 857–870, 2016.

[18] A. Mehmood, S. Yang, Z. Feng, M. Wang, A. S. Ahmad, R. Khan, M. Maqsood, and M. Yaqub, A transfer learning approach for early diagnosis of Alzheimer's disease on MRI images, *Neuroscience*, vol. 460, pp. 43–52, 2021.

[19] J. C. Mundt, D. M. Freed, and J. H. Greist, Lay person-based screening for early detection of Alzheimer's disease: Development and validation of an instrument, *Journals of Gerontology*: *Series B*, *Psychological Sciences and Social Sciences*, vol. 55, no. 3, pp. 163–170, 2000.

[20] H. Nawaz, M. Maqsood, S. Afzal, F. Aadil, I. Mehmood, and S. Rho, A deep feature-based real-time system for Alzheimer disease stage detection, *Multimedia Tools and Applications*, vol. 80, nos. 28&29, pp. 35789–35807, 2021.

[21] S. Naz, A. Ashraf, and A. Zaib, Transfer learning using freeze features for Alzheimer neurological disorder detection using ADNI dataset, *Multimedia Systems*, vol. 28, no. 1, pp. 85–94, 2022.

[22] M. Odusami, R. Maskeliūnas, and R. Damaševičius, An intelligent system for early recognition of Alzheimer's disease using neuroimaging, *Sensors*, vol. 22, no. 3, p. 740, 2022.

[23] B. Oltu, M. F. Akşahin, and S. Kibaroğlu, A novel electroencephalography based approach for Alzheimer's disease and mild cognitive impairment detection, *Biomedical Signal Processing and Control*, vol. 63, p. 102223, 2021.

[24] U. Raghavendra, U. R. Acharya, and H. Adeli, Artificial intelligence techniques for automated diagnosis of neurological disorders, *European Neurology*, vol. 82, nos. 1–3, pp. 41–64, 2019.

[25] E. Ruiz, J. Ramírez, J. M. Górriz, J. Casillas, and Alzheimer's Disease Neuroimaging Initiative, Alzheimer's disease computer-aided diagnosis: Histogram-based analysis of regional MRI volumes for feature selection and classification, *Journal of Alzheimers Disease*, vol. 65, no. 3, pp. 819–842, 2018.

[26] A. G. Sanchez-Reyna, J. M. Celaya-Padilla, C. E. Galván-Tejada, H. Luna-García, H. Gamboa-Rosales, A. Ramirez-Morales, J. I. Galván-Tejada, and Alzheimer's Disease Neuroimaging Initiative, Multimodal early Alzheimer's detection, a genetic algorithm approach with support vector machines, *Healthcare*, vol. 9, no. 8, p. 971, 2021.

[27] S. Klöppel, A. Abdulkadir, C. R. Jack Jr., N. Koutsouleris, J. Mourão-Miranda, and P. Vemuri, Diagnostic neuroimaging across diseases, *Neuroimage*, vol. 61, no. 2, pp. 457–463, 2012.

[28] S. Sarraf and J. Sun, Functional brain imaging: A comprehensive survey, arXiv preprint arXiv: 1602.02225, 2016.

[29] M. A. Warsi, W. Molloy, and M. D. Noseworthy, Correlating brain blood oxygenation level dependent (BOLD) fractal dimension mapping with magnetic resonance spectroscopy (MRS) in Alzheimer's disease, *Magnetic Resonance Materials in Physics, Biology and Medicine*, vol. 25, no. 5, pp. 335–344, 2012.

[30] H. I. Suk and D. Shen, Deep learning-based feature representation for AD/MCI classification, in *Proc.16th International Conference on Medical Image Computing and Computer-Assisted Intervention*, Nagoya, Japan, 2013, pp. 583–590.

[31] S. Sarraf, D. D. Desouza, J. A. E. Anderson, and C. Saverino, MCADNnet: Recognizing stages of cognitive impairment through efficient convolutional fMRI and MRI neural network topology models, *IEEE Access*, vol. 7, pp. 155584–155600, 2019.

[32] J. Zhang, Y. Gao, Y. Gao, B. C. Munsell, and D. Shen, Detecting anatomical landmarks for fast Alzheimer's disease diagnosis, *IEEE Transactions on Medical Imaging*, vol. 35, no. 12, pp. 2524–2533, 2016.

[33] M. K. Ojha, S. Wadhwani, A. K. Wadhwani, and A. Shukla, Automatic detection of arrhythmias from an ECG signal using an auto-encoder and SVM classifier, *Physical and Engineering Sciences in Medicine*, vol. 45, pp. 665–674, 2022.

[34] IDA, https://ida.loni.usc.edu/login.jsp?project=ADNI&page=HOME, 2022.

Gargi Pant Shukla received the PhD degree from Banasthali University Rajasthan. She is working as an associate professor at Doon Business School, Dehradun, India. She is a prolific trainer and researcher. She has presented and published over 25 research papers in places of international repute including IIM Lucknow, IIT Delhi, and IIT Roorkee. She is an expert in conducting experiential learning based training and development programs in the area of financial inclusion and planning. She is an SEBI certified trainer for imparting financial education in different sections of society. She has published her various research papers in ABDC "C" Category, Scopus, and UGC Care list.

Ankit Kumar is working as an assistant professor at the Department of Computer Engineering and Applications, GLA University, Mathura. His research area is in wireless sensor networks. He has published multiple papers in Taylor and Francis's different journals related to networks. His articles are published in 54 international journals and 11 national journals. He has received 8 patents. His work has been profiled broadly, such as information security, cloud computing image processing, neural network, and network. His research interests include computer network information security, computational model, compiler design, and data structure. He is a reviewer and editor of many reputed journals.

Santosh Kumar received the PhD, MPhil, and MBA degrees from Birla Institute of Technology, Mesra. He is working as an associate professor with Jaipuria Institute of Management, Jaipur. He is a prolific writer and published 40+ research papers, articles, and chapters in international peer-reviewed journals indexed in Scopus, ABDC, etc. He has presented papers at many international conferences. His research interest is in finance and technology area.

Rohit Agarwal is presently working as an associate professor at the Department of Computer Engineering and Applications, GLA University, Mathura. He has vast experience in the field of teaching and research. He has published more than 30 research papers in reputed international and national journals. His areas of research include vehicular network, digital image processing, machine learning, and time series data analysis.

Saroj Kumar Pandey received the BTech degree from University of Allahabad in 2008, the MTech (computer technology) degree from National Institute of Technology Raipur in 2011, and the PhD (information technology) degree from National Institute of Technology Raipur in 2021. He is serving as an assistant professor at the Department of Computer Engineering and Applications, GLA University, Mathura. He has published more than 20 research papers in international and national journals and conferences. He also published four book chapters in reputed publication. His areas of research include deep learning, machine learning, biomedical healthcare system, expert systems, neural networks, hybrid computing, and soft computing. He has guided various research projects in UG level.

Neeraj Varshney is presently working as an assistant professor at the Department of Computer Engineering and Applications, GLA University, Mathura. He is pursuing the PhD degree. He received the MTech and MCA degrees. He has vast experience in the field of teaching and research. He has published more than 20 research papers in reputed international and national journals. His areas of research include vehicular network, digital image processing, machine learning, and time series data analysis.