IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 13, No. 2, June 2024, pp. 1272~1281
ISSN: 2252-8938, DOI: 10.11591/ijai.v13.i2.pp1272-1281

Brain magnetic resonance imaging image classification for Alzheimer's disease and its hardware acceleration

Bettadapura A. Sujathakumari, Sudarshan Patil Kulkarni, Vikas Hallikeri
Department of Electronics and Communication Engineering, Sri Jayachamarajendra College of Engineering, JSS Science and Technology University, Mysuru, India

Article Info

Article history:

Received Jan 7, 2023
Revised Aug 21, 2023
Accepted Oct 31, 2023

Keywords:

Alzheimer's disease
Biomarkers
Classification
Magnetic resonance imaging
Segmentation

ABSTRACT

Alzheimer's is a progressive neurodegenerative disorder and is considered the sixth leading cause of death after cancer and heart attack. Early detection and diagnosis provide individuals to go through a wider variety of clinical trials and get multiple medical benefits. Research on the application of deep learning and machine learning to the early detection of Alzheimer's disease has recently gained considerable attention. In this paper, we propose a deep learning classification framework to classify the individual with different progression stages of Alzheimer's disease such as mild cognitive impairment (MCI) and cognitive normal (CN). The dataset from Alzheimer's disease neuroimaging initiative (ADNI) is considered in this paper which is a multisite having collection of Neuroimaging data for researchers. Structural magnetic resonance imaging (MRI) images are considered from the ADNI data set and feature extraction is done using a 2D discrete wavelet transform. 97% of data reduction is achieved during data pre-processing. The algorithm is trained and validated. The algorithm is accelerated in Nvidia Tx2 graphics processing unit (GPU) to get the better throughput. The result shows our algorithm outperforms the other deep learning algorithms with 91.56% accuracy.

This is an open access article under the CC BY-SA license.

Corresponding Author:

Bettadapura A. Sujathakumari
Department of Electronics and Communication Engineering, Sri Jayachamarajendra College of Engineering
JSS Science and Technology University
Mysuru, Karnataka, India
Email: basujatha_12@rediffmail.com

1. INTRODUCTION

Alzheimer's disease (AD) has evolved into a very challenging illness in recent years that finally leads to the death of the individual. Alzheimer's disease initially affects brain functioning which finally destroys memory the predominant type of dementia, Alzheimer's disease accounts for 60–70% of cases. The disease cannot be prevented, cured or destroyed. AD is prevalent in persons over 65. Effects of Alzheimer's 1 in 14 persons over 65 and 1 in 6 people over 80 have diabetes, respectively. Over 5.3 million people live with dementia in India of which Alzheimer's is the prime factor. At present deep learning the development of a computer-aided brain illness detection system using structural magnetic resonance imaging has made extensive use of classification frameworks. Recently, a number of methods for the diagnosis of AD have been developed employing deep learning and image processing methods, which work more effectively than manual systems.

Overcoming the problem of small sample size in AD detection [1]. Using just limited data sets, this approach significantly increased classification accuracy. They proposed machine-learning models are proposed to identify the various stages of AD based on broad learning systems (BLS) [2]. Here they used a robust deep learning system was built to identify different stages of AD based on magnetic resonance imaging (MRI) and positron emission tomography (PET) scans [3]. They proposed a novel domain transfer method to classify the

mild cognitive impairment (MCI) prediction was achieved [4], [5]. This method contains two-component mainly the adapted support vector machine and the cross-domain kernel learning for transferring auxiliary domain knowledge. They focused on developing a new algorithm to distinguish people with MCI or Alzheimer's disease (AD) from healthy controls (NC) [6], [7]. The experiment shows that through multi-feature fusion better performance can be achieved. Here it is proposed a cutting-edge computer-aided diagnosis system that analyses structural magnetic resonance imaging utilising feature ranking and a genetic algorithm [8], [9]. The proposed system can distinguish between progressive mild cognitive impairment (pMCI) and stable mild cognitive impairment (sMCI) patients and is appropriate for practical use in clinical settings. They used different machine learning algorithms for comparing automated methods for hippocampal segmentation [9]–[12]. Here they experimented with different hippocampal segmentation and found that accuracy depends on different factors such as the size of the training set. It is considered the clinical data to predict the progression of AD [13]–[15]. Machine learning models were trained on the clinical data and validated using a separate testing data set. They analysed methods for machine learning and data mining created for biomedical informatics (BMI) [16]–[19]. They tested a scalable and effective hardware acceleration technique for this aim by integrating a server architecture with inexpensive FPGAs. Here it mainly focuses on developing a using deep learning, a quick and precise way is available to guess a subject's age [20]–[23]. This algorithm is used to accelerate over the graphics processing unit (GPU). They proposed a convolutional neural network (CNN) implementation of image processing. Here they accelerate the CNN over Nvidia's Fermi architecture [24]–[26].

Considering the different papers in the study, data pre-processing stage feature extraction is the important phase that becomes the input to the system. Different methods such as discrete wavelet transform (DWT) and principal component analysis (PCA) method are used for feature extraction. It was observed from one of the approaches that, the deep learning methods are giving good accuracy compared with the machine-learning algorithm. Structural MRI, Functional MRI, and PET scan were seen as being important indicators of Alzheimer's disease. Different hardware such as GPU and field programmable gate array (FPGA) can be used as an edge device for effectively implementing the neural network.

2. PROPOSED WORK

This section explains the project's proposed work. Data collection is done in the first step via the Alzheimer's disease neuroimaging initiative (ADNI) website. The age category is used to choose the data, not the gender distinction. Data is divided depending on the basis patient id for a three-year follow-up line to be processed later. The obtained data collection is subsequently segmented to eliminate an undesirable portion of the brain, primarily skull stripping. The brain MRI's registration is done with the common montreal neurological institute (MNI) template concurrently with segmentation. For the analysis, either the entire MRI in 3-dimension (3D) or 2-dimension (2D) slices might be employed. The work takes into consideration the extracted 2D slice. In the proposed study, the feature extraction and reduction are done using multilevel 2-dimensional discrete wavelet transform (2D-DWT). For the prediction and categorization of the various phases of Alzheimer's disease, the deep learning classifier is taken into consideration. Figure 1 shows the block diagram of proposed work. Training the classier comes after selection, segmentation, and feature extraction. The testing set verifies the classifier model while the training set is utilised to train the algorithm. The classifier's accuracy result shows how well the data has been categorised for the various phases of Alzheimer's disease.

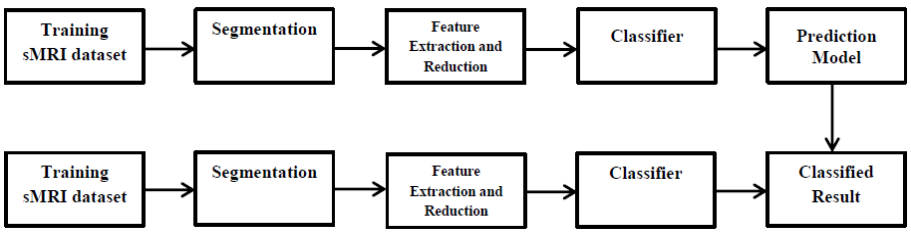

Figure 1. Block diagram of proposed work

2.1. Method

The proposed methodology of the project is explained in this section. The flow chart for the process is given in Figure 2. Data collection from a normal ADNI dataset is the first stage of the project. In particular, data from ADNI-1, which contains patient year-level data, is retrieved. ADNI contains information and samples

from MRI scans, blood biomarkers, cerebrospinal fluid (CSF) biomarkers, cognitive test results, and PET scans. The ADNI website offers study materials and data from the North American ADNI project, which also includes information about AD patients, MCI participants, and cognitive normal (CN). The following data is mostly taken into account for the project's study. CN: Participants in the 1.5T 3-year data. MCI: 1.5T 3-year data subjects. 3D data will be retrieved via the ADNI (3-dimensional). From the assistance of micro software, which aids in the visualisation of the Nifti and analysis format files, the three distinct views of an MRI picture can be observed.

2.2. Details of the dataset

From ADNI 1, 2,182 MRI image samples were obtained. These 1.5T, T1-weighted, 3-year MRI pictures are available. The total number of patients in the ADNI 1 dataset is displayed in Table 1. Because the aim of our study is early diagnosis and AD prediction, only the CN and MCI data sets have been taken into account for testing and training the algorithm. After further deleting the MRI images and just taking into consideration the CN and MCI images, the following number of total samples and samples for training and testing were obtained, as shown in Table 2. Figure 2 shows the flowchart of the process.

Table 1. Number of samples from the ADNI dataset

Subjects	No. of samples
CN	750
MCI	981
AD	541

Table 2. Number of CN and MCI samples taken for classification

Subjects	Total samples	Samples for Testing	Samples for Training
CN	205	20	185
MCI	343	34	309

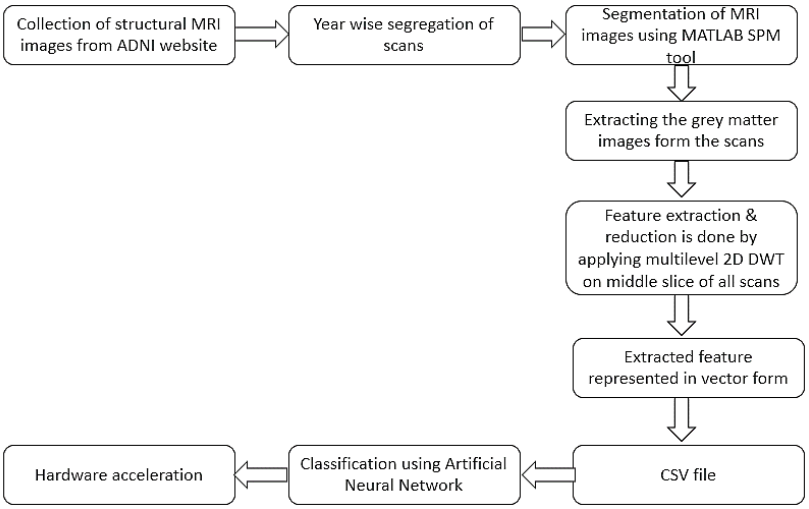

Figure 2. Flow chart of the process

The data pre-processing is done using MATLAB software. The spectroscopic magnetic resonance imaging (sMRI) image samples consisting of different stages of Alzheimer's disease are given as input to the SPM tool and the grey matter image is extracted. Further, each image is converted into vector form and stored in the CSV file. Further, the feature extraction and data reduction are done using discrete wavelet transform (DWT). The feature extraction is done using the python algorithm. PyWavelets library is used for the multilevel DWT and inverse discrete wavelet transform (IDWT). By using PyWavelets computing approximations of wavelet and scaling is efficient. By feature extraction, the vector size is reduced and is stored in the comma-separated values (CSV) format. This becomes the input for the algorithm. Deep learning frameworks such as artificial neural network (ANN) and CNN are built and are trained using the dataset. The parameters are tuned to get better accuracy.

2.3. Segmentation

Following the separation based on their ID of a patient's MRI, segmentation is a crucial step. Segmentation is a feature selection method that removes the data, which are irrelevant from the MRI image. Figure 3 shows the segmented grey matter of CN subject and Figure 4 shows the segmented grey matter of MCI subject, which depict the segmented grey matter of CN and MCI patients, respectively.

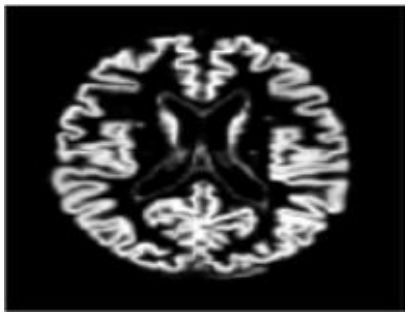

Figure 3. Segmented grey matter of CN subject

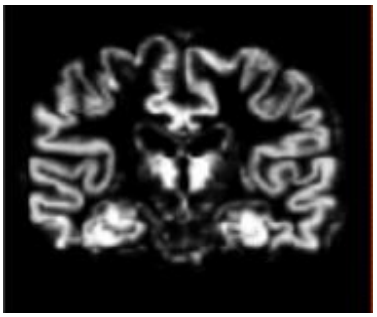

Figure 4. Segmented grey matter of MCI subject

2.4. Feature extraction and reduction

The feature extraction technique is then applied to the segmented images to extract the required characteristics that serve as the foundation for classification and prediction after the unneeded parts of the brain MRI have been removed using segmentation. The features will be retrieved using the feature extraction method as a matrix, which will then be reduced to a matrix with fewer dimensions without affecting the characteristics of the extracted features as a whole. Figure 5 depicts a two level 2D DWT decomposition where 4 sub bands are obtained at the first level and 7 sub bands at the second level. From this pair of diagonal coefficients, one approximation coefficient, also acquired are horizontal and vertical coefficients. A collection of diagonals, horizontal, and vertical coefficients collectively referred to as detailed coefficients is not taken into consideration in the study. As opposed to the high-pass filter coefficients (HPF coefficients), the low-pass filter coefficients (LPF coefficients) are more significant and are further taken into consideration in the job.

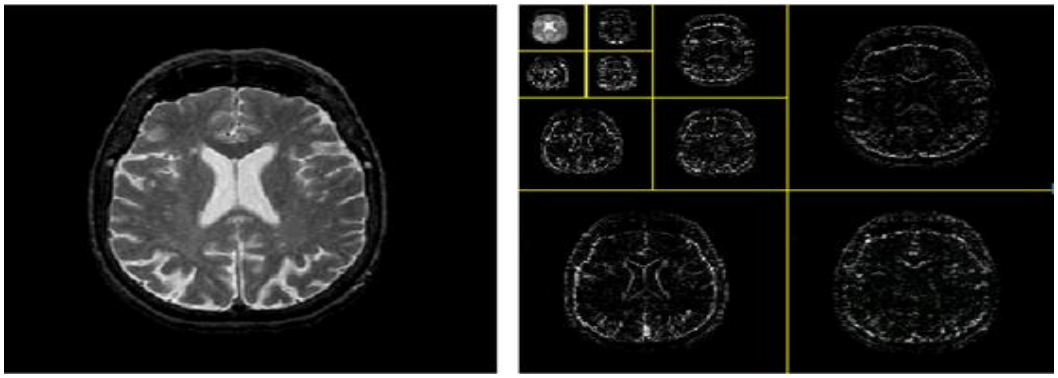

Figure 5. Two-level 2D DWT decomposition process

2.5. Classification

An artificial neural network (ANN) also called a neural network is the computing system that works the way the brain performs a particular task. Neural network learns from the data and will have the ability to decide on the new input data. ANN consists of a fundamental unit as Neuron. ANN is mainly made of three layers. named as input layer, hidden layer and output layer. The input layer receives the external data for pattern recognition. Hidden layers learn from the data. The output layer gives the solution to the new data. ANN receives the signal and shoots it to neurons connected to it. The signal is the real number. The connections between the neurons are called weights. These weights get adjusted during the training from the data. The output of the neuron is calculated from the nonlinear function. ANN uses the backpropagation algorithm to modify the weights for better prediction. The ANN architecture is given in Figures 6 and 7.

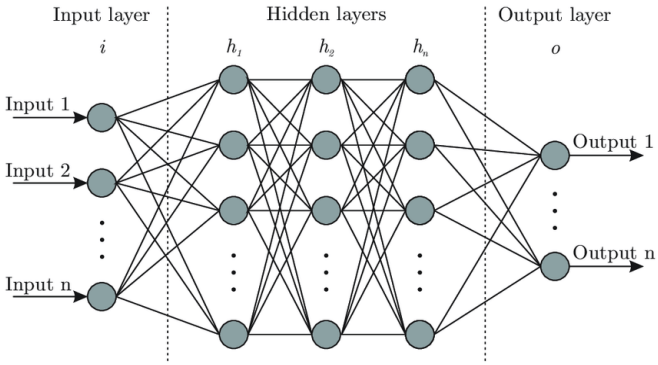

Figure 6. ANN architecture

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 1200)              2983200
_________________________________________________________________
module_wrapper (ModuleWrappe (None, 1200)              0
_________________________________________________________________
dense_1 (Dense)              (None, 1200)              1441200
_________________________________________________________________
module_wrapper_1 (ModuleWrap (None, 1200)              0
_________________________________________________________________
dense_2 (Dense)              (None, 300)               360300
_________________________________________________________________
dense_3 (Dense)              (None, 150)               45150
_________________________________________________________________
module_wrapper_2 (ModuleWrap (None, 150)               0
_________________________________________________________________
dense_4 (Dense)              (None, 1)                 151
=================================================================
Total params: 4,830,001
Trainable params: 4,830,001
Non-trainable params: 0
```

Figure 7. ANN layer architecture

2.6. Hardware acceleration

The algorithm is initially implemented in the central processing unit (CPU) based environment. GPU is a powerful computational resource for implementing neural networks. Initially, the algorithm is trained and tested on the CPU. To deploy the neural network in the edge device the NVidiaTx2GPU is used. NVidia Jetson TX2 is the power-efficient graphical processing unit used for embedded AI computing devices. The computational time is compared and calculated. The specification of Nvidia TX2 and CPU used is shown in Table 3.

Table 3. Specification of GPU and CPU

Specification	CPU	GPU
Processor	Intel Core i5	ARM cortex A57
Cores	4	256
RAM	12.0 GB	4GB
System type	64 Hit	64 Hit
Frequency	2.40 GHz	1.2 GHz

3. RESULTS AND DISCUSSION

In this study, a mixture of structural brain imaging that has been previously processed has been taken into account as input for the classifier algorithm. High classification performance was attained using this dataset. The classification of the sMRI data-CN and MCI-considered for the study allowed for the analysis of prediction accuracy.

3.1. Comparison of accuracy

It is analyzed that classification accuracy is not much as the number of features in the training set is reduced. The sklearn library, which divided the data into train and test sets, provided this information. It was discovered that employing DWT reduced the features by about 75%. The time complexity for classification decreased as the number of features dropped. The classification algorithm's precision was unaffected by this, though. In certain instances, utilizing 2D DWT actually did enhance the categorization accuracy. Table 4 displays the accuracy comparison between CN and MCI.

3.1.1. Biomarker and clinical data

Biomarkers track a cell's motions. They are crucial for the early detection of anomalies in the healthcare system. Therefore, biomarkers aid in the early prediction of any nervous system or cognitive problem. The ability of many biomarkers to identify AD in its early stages is being researched. Tau and beta-amyloid concentrations in CSF are taken into account in our research. According to research, variations in CSF levels of the protein's tau and beta-amyloid. These are closely associated to Alzheimer's, can be used to diagnose AD in its early stages. For the purpose of disease prediction in the work, additional clinical data are taken into account in addition to CSF biomarkers. Mini-mental state examination (MMSE) score, age, gender, education level, and genetic information like apolipoprotein-4 are all part of the clinical data. For the proposed work, all of the aforementioned clinical data and CSF biomarkers are combined with 2D-DWT wavelets to produce better results than if they were used alone. The classifiers get the combined data in order to make a prediction. Table 5 compares the accuracy of ANN with biomarkers versus without biomarkers.

Table 4. Comparison of accuracies for classification

Model	Accuracy
ANN	91.56%
CNN	80.72%

Table 5. Accuracy comparison for classification with and without biomarker

Model	Accuracy
ANN with biomarker	91.56%
ANN without Biomarker	84.33%

3.2. Contrasting additional performance indicators

The ANN model was further evaluated using different performance metrics such as specificity, sensitivity, accuracy, error rate, false-positive rate, and confusion metrics are also known as classification metrics. Confusion metrics: A confusion matrix is a performance measurement table that is used to depict the performance of a classification model on a set of test data for which the true values are known. Figure 8 describes the confusion metrics.

- Specificity: Specificity is also called true negative rate (TNR). Specificity is the ratio of the number of correct negative predictions to the total number of negatives. The best specificity is 1.0, whereas 0.0 is the worst.
- Precision: Additionally, called as positive predictive value, precision (PPV). It is the proportion of all positively expected observations to those that were successfully predicted. The best precision is 1.0, while the poorest is 0.0.
- Sensitivity: It is sometimes referred to as true positive rate or recall (TPR). The ratio of the number of accurate positive forecasts to the overall number of positives is known as sensitivity. The best sensitivity is 1.0, while the poorest is 0.0.
- Error rate (ERR): The number of all inaccurate predictions divided by the total number of observations in the dataset yields the error rate (ERR). Error rates range from 0.0 to 1.0, with 1.0 being the worst. The confusion metrics of ANNwith biomarker and without biomarker are shown in Figures 9 and 10. Confusion metrics of CNN is shown in Figure 11. Other performance metrics have been calculated using the confusion matrix. The comparison of performance metrics obtained from ANN and CNN is shown in Table 6.

$$Specificity = TN / (TN + FP) \quad (1)$$

$$Precision = TP/TP + FP \quad (2)$$

$$Sensitivity = TP / (FN + TP) \quad (3)$$

$$Error = FP + FN/(TP + TN + FP + FN) \quad (4)$$

		Predicted Class	
		Positive	**Negative**
Actual Class	**Positive**	True Positives (TP)	False Negatives (FN)
	Negative	False Positives (FP)	True Negatives (TN)

Figure 8. Confusion metrics

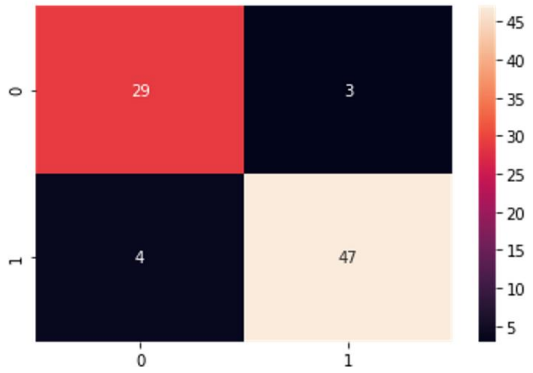

Figure 9. Confusion metrics of ANN with biomarker

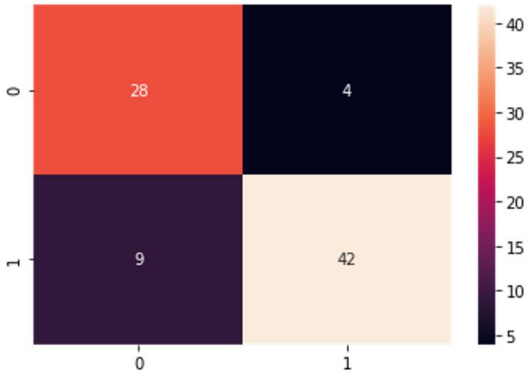

Figure 10. Confusion metrics of ANN without biomarker

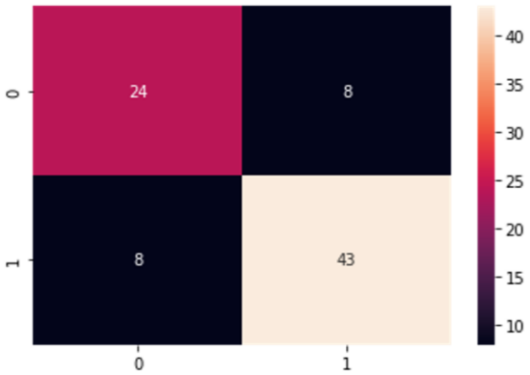

Figure 11. Confusion metrics of CNN

Table 6. Comparison of performance metrics

Parameters	ANN with biomarkers	ANN without biomarkers	CNN
Sensitivity	0.92	0.82	0.84
Specificity	0.90	0.87	0.77
error	0.08	0.15	0.19
precision	0.94	0.91	0.84

From the performance metrics, it is clear that ANN with biomarkers has higher specificity, sensitivity, precision and lesser error than other algorithms. This depicts that ANN with biomarkers is a better classifier than ANN without biomarkers and CNN. Receiver operating characteristic (ROC) curve shows the performance of a classification model at all classification thresholds. The area under the curve (AUC), shows

the performance of a binary classifier on all possible threshold values. Their curves obtained with ANN with biomarkers are shown in Figure 12. The ROC curves obtained with ANN with biomarker and CNN are shown in Figures 13 and 14. The area under the curve (AUC) is the measure of the ability of a classifier to distinguish between classes and is used as a summary of the ROC curve. The AUC curve of ANN with biomarkers and without biomarkers is shown in Figures 15 and 16. The AUC curve of CNN is shown in Figure 17.

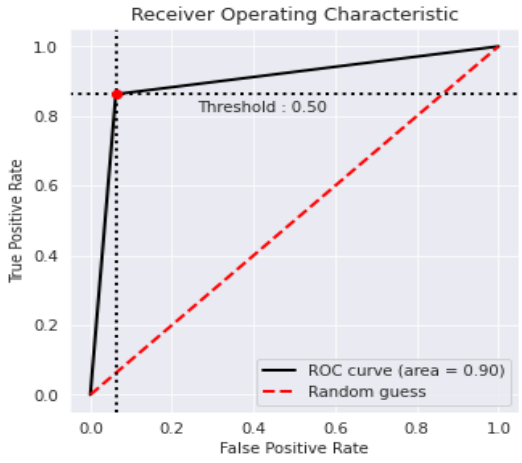

Figure 12. ROC curve for ANN with biomarker

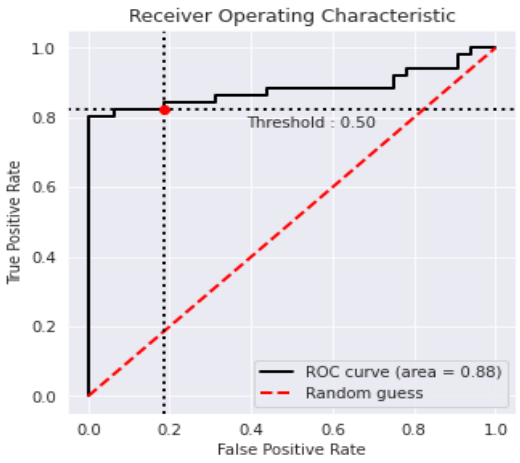

Figure 13. ROC curve for ANN without biomarker

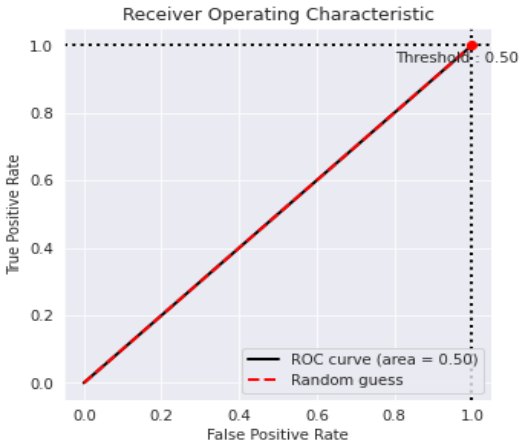

Figure 14. ROC curve for CNN

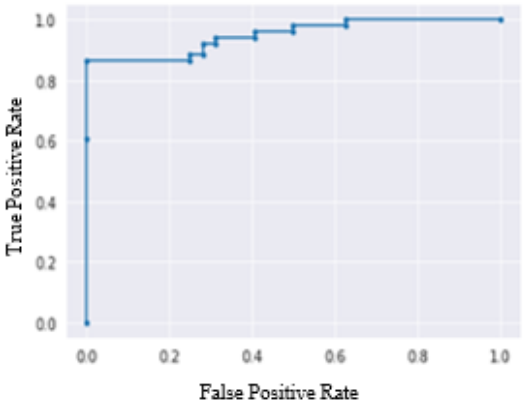

Figure 15. AUC curve for ANN with biomarker

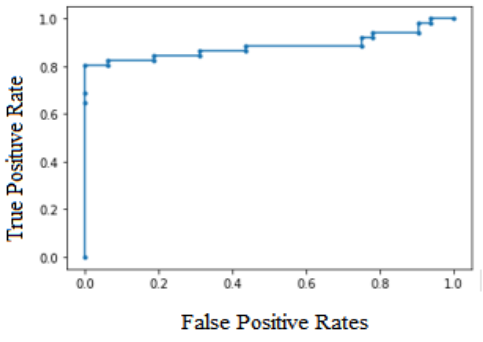

Figure 16. AUC curve for ANN without biomarker

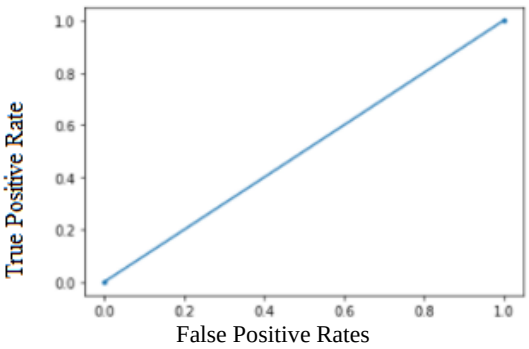

Figure 17. AUC curve for CNN

Classification accuracy of 80.72% was obtained with a CNN and 92.56% with Artificial Neural Network. Thus, the most effective performance for classification and prediction comes from artificial neural networks. It was found from the classifier findings that the ANN was more effective and performed better. The presented work demonstrates the classification of CN and MCI stages of AD. The model was able to classify the algorithm with 91.56%. Further, the model was implemented in the edge hardware Nvidia Tx2. The computation speed and throughput were improved. Thus, this project encourages the importance of detecting Alzheimer's disease at an earlier stage and also building a standalone system for the diagnosis. The comparison of throughput is shown in Table 7. The presented GPU implementation is significantly 2.33 times faster during training and 1.5 times during testing compared to the CPU implementation.

Table 7. GPU Throughput

	CPU	GPU
Training	7u s	3u s
Testing	3u s	2u s

4. CONCLUSION

In the paper, the neuroimaging data of different stages of Alzheimer's disease is considered and deep learning frameworks such as ANN and CNN are trained for tested for better predictive accuracy. In the data pre-processing phase extraction of grey matter images from 3-D MRI, Images was done and by applying the feature, extraction technique such as 2d DWT 97% of data reduction was achieved. Neural network architecture such as ANN and CNN were trained, tested, and obtained the accuracy of 91.56% and 84.33% respectively. Finally, the algorithm was deployed on Nvidia GPU and throughput of 2.33 times faster during training and 1.5 times during testing compared to CPU implementation was achieved.

REFERENCES

[1] W. Li, Y. Zhao, X. Chen, Y. Xiao, and Y. Qin, "Detecting Alzheimer's disease on small dataset: A knowledge transfer perspective," *IEEE Journal of Biomedical and Health Informatics*, vol. 23, no. 3, pp. 1234–1242, May 2019, doi: 10.1109/JBHI.2018.2839771.

[2] R. Han, C. L. P. Chen, and Z. Liu, "A novel convolutional variation of broad learning system for Alzheimer's disease diagnosis by using MRI images," *IEEE Access*, vol. 8, pp. 214646–214657, 2020, doi: 10.1109/ACCESS.2020.3040340.

[3] F. Li, L. Tran, K. H. Thung, S. Ji, D. Shen, and J. Li, "A robust deep model for improved classification of AD/MCI patients," *IEEE Journal of Biomedical and Health Informatics*, vol. 19, no. 5, pp. 1610–1616, Sep. 2015, doi: 10.1109/JBHI.2015.2429556.

[4] S. Basheer, S. Bhatia, and S. B. Sakri, "Computational modeling of dementia prediction using deep neural network: Analysis on oasis dataset," *IEEE Access*, vol. 9, pp. 42449–42462, 2021, doi: 10.1109/ACCESS.2021.3066213.

[5] B. Cheng, M. Liu, D. Shen, Z. Li, and D. Zhang,, "Multi-domain transfer learning for early diagnosis of Alzheimer's disease," *Neuroinformatics*, vol. 15, no. 2, pp. 115–132, Dec. 2017, doi: 10.1007/s12021-016-9318-5.

[6] Z. Xiao, Y. Ding, T. Lan, C. Zhang, C. Luo, and Z. Qin, "Brain MR image classification for Alzheimer's disease diagnosis based on multifeature fusion," *Computational and Mathematical Methods in Medicine*, vol. 2017, pp. 1–13, 2017, doi: 10.1155/2017/1952373.

[7] I. Beheshti, H. Demirel, and H. Matsuda, "Brain MR image classification for alzheimer's disease diagnosis based on multifeature fusion," *Computers in Biology and Medicine*, vol. 83, pp. 109–119, Apr. 2017, doi: 10.1016/j.compbiomed.2017.02.011.

[8] J. H. Morra, Z. Tu, L. G. Apostolova, A. E. Green, A. W. Toga, and P. M. Thompson, "Comparison of adaboost and support vector machines for detecting alzheimer's disease through automated hippocampal segmentation," *IEEE Transactions on Medical Imaging*, vol. 29, no. 1, pp. 30–43, Jan. 2010, doi: 10.1109/TMI.2009.2021941.

[9] K. Neshatpour *et al.*, "Big biomedical image processing hardware acceleration: A case study for K-means and image filtering," in *Proceedings - IEEE International Symposium on Circuits and Systems*, May 2016, vol. 2016-July, pp. 1134–1137, doi: 10.1109/ISCAS.2016.7527445.

[10] T. W. Huang *et al.*, "Age estimation from brain MRI images using deep learning," in *Proceedings - International Symposium on Biomedical Imaging*, Apr. 2017, pp. 849–852, doi: 10.1109/ISBI.2017.7950650.

[11] E. László, P. Szolgay, and Z. Nagy, "Analysis of a GPU based CNN implementation," Aug. 2012, doi: 10.1109/CNNA.2012.6331451.

[12] S. H. Sreedhara, V. Kumar, and S. Salma, "Efficient big data clustering using adhoc fuzzy c means and auto-encoder CNN," in *Lecture Notes in Networks and Systems*, vol. 563, Springer Nature Singapore, 2023, pp. 353–368.

[13] X. Guo *et al.*, "A computational Monte Carlo simulation strategy to determine the temporal ordering of abnormal age onset among biomarkers of Alzheimer's disease," *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, vol. 19, no. 5, pp. 2613–2622, Sep. 2022, doi: 10.1109/TCBB.2021.3106939.

[14] G. Lee *et al.*, "Predicting Alzheimer's disease progression using multi-modal deep learning approach," *Scientific Reports*, vol. 9, no. 1, 2019, doi: 10.1038/s41598-018-37769-z.

[15] S. Belleville, C. Fouquet, S. Duchesne, D. L. Collins, and C. Hudon, "Detecting early preclinical alzheimer's disease via cognition, neuropsychiatry, and neuroimaging: Qualitative review and recommendations for testing," *Journal of Alzheimer's Disease*, vol. 42, no. s4, pp. S375–S382, Oct. 2014, doi: 10.3233/JAD-141470.

[16] P. M. Petrone *et al.*, "Prediction of amyloid pathology in cognitively unimpaired individuals using voxel-wise analysis of longitudinal structural brain MRI," *Alzheimer's Research and Therapy*, vol. 11, no. 1, Aug. 2019, doi: 10.1186/s13195-019-0526-8.

[17] P. J. Moore, T. J. Lyons, and J. Gallacher, "Random forest prediction of Alzheimer's disease using pairwise selection from time series data," *PLoS ONE*, vol. 14, no. 2, p. e0211558, Feb. 2019, doi: 10.1371/journal.pone.0211558.

[18] T. Wang, R. G. Qiu, and M. Yu, "Predictive modeling of the progression of Alzheimer's disease with recurrent neural networks," *Scientific Reports*, vol. 8, no. 1, Jun. 2018, doi: 10.1038/s41598-018-27337-w.
[19] C. Salvatore, A. Cerasa, and I. Castiglioni, "MRI characterizes the progressive course of AD and predicts conversion to Alzheimer's dementia 24 months before probable diagnosis," *Frontiers in Aging Neuroscience*, vol. 10, no. MAY, May 2018, doi: 10.3389/fnagi.2018.00135.
[20] R. K. Garg, A. Kulshreshtha, and M. T. Scholar, "A review of automated MRI image processing techniques employing segmentation and classification," *International Journal of Computer Science Trends and Technology*, vol. 5, no. 2, pp. 117–120, 2013, [Online]. Available: www.ijcstjournal.org.
[21] F. Segovia *et al.*, "A comparative study of feature extraction methods for the diagnosis of Alzheimer's disease using the ADNI database," *Neurocomputing*, vol. 75, no. 1, pp. 64–71, Jan. 2012, doi: 10.1016/j.neucom.2011.03.050.
[22] F. Song, Z. Guo, and D. Mei, "Feature selection using principal component analysis," in *Proceedings - 2010 International Conference on System Science, Engineering Design and Manufacturing Informatization, ICSEM 2010*, Nov. 2010, vol. 1, pp. 27–30, doi: 10.1109/ICSEM.2010.14.
[23] N. Kumaran and R. Bhavani, "PCA-based feature selection for MRI image retrieval system using texture features," in *Advances in Intelligent Systems and Computing*, vol. 324, Springer India, 2015, pp. 109–117.
[24] K. S. Biju, S. S. Alfa, K. Lal, A. Antony, and M. K. Akhil, "Alzheimer's detection based on segmentation of MRI image," *Procedia Computer Science*, vol. 115, pp. 474–481, 2017, doi: 10.1016/j.procs.2017.09.088.
[25] C. Mishra and D. L. Gupta, "Deep Machine Learning and Neural Networks: An Overview," *IAES International Journal of Artificial Intelligence (IJ-AI)*, vol. 6, no. 2, p. 66, Jun. 2017, doi: 10.11591/ijai.v6.i2.pp66-73.
[26] A. Rana, A. S. Rawat, A. Bijalwan, and H. Bahuguna, "Application of multi layer (perceptron) artificial neural network in the diagnosis system: A systematic review," Aug. 2018, doi: 10.1109/RICE.2018.8509069.

BIOGRAPHIES OF AUTHORS

Bettadapura A. Sujathakumari is currently working as Associate Professor in Department of Electronics and Communication Engineering, SJCE (JSS-STU), Mysuru, Karnataka, India. She received the B.E degree in Electronics and Communication Engineering from University of Mysuru in 1990, the MTech degree in Industrial Elelctronics from SJCE Mysuru in 1999. Her research interest includes Signal Processing, Image Processing and Machine Learning. She can be contacted at email: basujatha_12@rediffmail.com.

Dr. Sudarshan Patil Kulkarni is currently working as Professor in Department of Electronics and Communication Engineering, SJCE (JSS-STU), Mysuru, Karnataka, India. He received the B.E degree in Electronics and Communication Engineering Karnatak University, India in 1996, ME in Electrical Engineering from Old Dominion University, Verginia, USA in 2000 and PhD from from Old Dominion University, Verginia, USA in 2004. His research interest includes Linear Nonlinear systems, Signal/Image Processing, Wavelets, Hybrid Control systems, Neural Networks and Deep Learning. He can be contacted at email: sudarshan_pk@sjce.ac.in.

Vikas Hallikeri has completed MTech in Industrial Electronics, Electronics and Communication Engineering Department, SJCE (JSS-STU), Mysuru, Karnataka, India. His research interests include Machine learning and Image Processing. He can be contacted at email: vikasfhallikeri7@gmail.com.