Exploring Neural Network Approaches for Alzheimer's Disease Detection: An Analysis of RNN and CNN Performance

Ritu Priya Singh
Computer Science and Engineering
Lovely Professional University
Jalandhar, India
rs9110131217@gmail.com

Sandeep Kumar*
Computer Science and Engineering
Lovely Professional University
Jalandhar, India
ssihag222@gmail.com

Fateh Singh Rana
Computer Science and Engineering
Lovely Professional University
Jalandhar, India
fatehsinghrana130302@gmail.com

Saloni Singh
Computer Science and Engineering
Lovely Professional University
Jalandhar, India
salonisingh1312@gmail.com

Akarsh Anand
Computer Science and Engineering
Lovely Professional University
Jalandhar, India
akarshharsh12@gmail.com

Dikshit Kukreja
Computer Science and Engineering
Lovely Professional University
Jalandhar, India
dikshitkukreja5@gmail.com

Neelesh Sharma
Computer Science and Engineering
Lovely Professional University
Jalandhar, India
neeleshsharma087@gmail.com

Abstract— Alzheimer's disease is a degenerative neurological ailment marked by memory loss, cognitive decline, and behavioral disturbances. It is the most common type of dementia, affecting millions of people globally, primarily the elderly. The disease is characterized by the formation of plaques and tangles in the brain, which disrupt neuronal communication and eventually lead to cell death. In this study, we analyze the use of machine learning models in the context of Alzheimer's disease, which were CNN and RNN. The RNN is a deep learning model that has been trained to interpret and transform sequential data inputs into particular sequential data outputs. However, CNNs are deep learning models that excel at identifying spatial correlations in data, which makes them a good fit for image analysis tasks like analyzing MRI scans, which are frequently utilized in AD research. We used datasets from the OASIS, which offers publicly available brain imaging datasets for Alzheimer's disease research, and from Kaggle, a well-known platform for data science competitions and cooperation, to train and assess these models. Our experimental results demonstrate the promising performance of the models on both datasets. During our work, On the OASIS dataset, CNN achieved 100% accuracy, whereas RNN achieved 73.15%. On the Kaggle dataset, the CNN model achieved 97.33% accuracy, while the RNN model achieved 80.67%.

Keywords— Alzheimer's Disease, Machine learning, Deep Learning, Convolutional Neural Network, Recurrent Neural Network

I. INTRODUCTION

In today's world, illness is the main concern. Numerous people deal with health difficulties daily. Every year, almost 10 million new cases of Alzheimer's disease are diagnosed, and the World Health Organization (WHO) estimates that the disorder affects more than 55 billion people worldwide. Dehydration, memory loss, thinking impairments, malnourishment, infection, pneumonia, and many other mental illnesses are among the mental health problems caused by Alzheimer's disease that ultimately result in mortality. People typically experience memory loss and other cognitive problems. Somewhere, this disease generally affects women. Alzheimer’s diseases are likely to develop through many factors like genetics, lifestyle, and environment. Around 5% of people in the age group 65-74, 13.1% of age 75-84 and 33.3% of age 85 and over are having this disease. Previously most of the diseases were not curable or people find the disease at the last stage. But, now in the modern era, problems or disease are being identified at the initial stages with the support of ML algorithms.

Machine learning algorithms are being used to develop accurate and reliable models for Alzheimer's disease (AD), enhancing diagnosis and medication outcomes. These models can be found on open platforms like Kaggle, OASIS, ADNI, Data-share, and hospitals. Most algorithms have 90% or higher accuracy, and their performance depends on how they are trained. Machine learning algorithms can be supervised or unsupervised, with supervised learning focusing on labeled data and unsupervised learning focusing on unlabeled datasets. Some of the highest accuracy levels include the 18-layered CNN, 98% accuracy rate, SVM, RF, LSTM, LR, Recurrent Neural Network (RNN), and Gradient Boosting Machines (GBM). One approach to developing an AD detection model is using neuroimaging data, such as MRI scans, to analyze brain structures and abnormalities. However, the complexity of diagnosing AD at its initial stages and the potential for subtle characteristics to be mistaken for normal signs of aging or other conditions make accurate diagnosis challenging. In this work, we put out a model that described how Alzheimer can be traced without causing any dangerous threat. Using CNN and RNN models for multiple tests. Not only will we be able to trace but can also be shared with medical experts to look on and proceed towards the cure.

II. Literature Review

The field of Alzheimer's Disease (AD) detection through machine learning (ML) strategies has seen significant advancements in recent years. In 2021, the Support Vector Machine (SVM) [1] was found to be the most effective algorithm for AD detection, achieving a notable accuracy of 92%. In 2022, a novel AD detection model based on EEG signals was introduced, utilizing the K-Nearest Neighbors (KNN) [2] algorithm with impressive accuracies of 100% and 92.01% in different cross-validation approaches. Convolutional Neural Network (CNN) [3] achieved a high accuracy of 90.8% through deep learning techniques. A Recurrent Neural Network (RNN) [4] yielded a notable accuracy of 95%. There is a diverse array of approaches for AD detection [5] and classification using ML methods. Jong Bin Bae et al. [6] investigated the efficacy of a CNN in AD classification using T1-weighted MRI scans, achieving accuracies of 88% and 89% for the ADNI and SNUBH datasets, respectively. Tang et al. [7] explored various ML algorithms for AD progression classification, with Random Forest (RF) yielding the topmost precision of 73.8% and superior AUC for CN-AD prediction. Rashmi Kumari [8] demonstrated the effectiveness of CNNs for early AD detection, achieving an accuracy of 90.25% using data from ADNI and OASIS datasets. Recent literature showcases various research endeavors aimed at enhancing AD prognosis, detection, and diagnosis through ML techniques. An et al. employed RF algorithms, achieving accuracy rates of up to 87%, emphasizing the potential of ML models in assessing AD treatment efficacy. Another author explored a two-stage DL model for AD detection and prediction, reporting accuracies of 82.82% and 92.01% using DT and RF algorithms, respectively. One of the research assessed DT, RF, SVM, LR, and KNN algorithms, revealing accuracies ranging from 71% to 83%.

TABLE I. Literature Review summary

Reference	Accuracy	Dataset	Limitations
[1]	SVM-92%, LR-74.7%, DT-80%, RF-81.3%	Kaggle & OASIS	Overfitting
[2]	KNN-92%	Data-share	Diverse populations and potential challenges in interpreting features of dataset
[3]	EL-73%, RT-92%, CNN-84.2%, DL_CNN-90.8%, SVM-68%, DL-85%, XGBoost-88%, RF-85%	ADNI, AIBL, NACC	Multidomain interventions may be burdensome and not universally acceptable
[4]	SVM, NN, DT-79%, RNN-95.6%, SVM-86%, SVM, RF-87-94%, NB-68%	Global Dementia Observatory	Enabling prompt intervention and better patient outcomes
[5]	NB-93.44%, ANN-83.56%, KNN-95.92%, SVM-96.12%	NA	To identify AD at very early stages is difficult
[6]	CNN_ADNI-88%, ANN_SNUBH-89%	ADNI & SNUBH	May not capture nuances of atrophy in other brain regions, potentially leading to misclassification
[7]	RF-73.8%, SVM-60.7%, DT-59.5%	ADNI	Sample size and prediction accuracy improvement
[8]	CNN-90.25%	ADNI & OASIS	Comparison with previous studies is limited
[9]	SVM-99.21%, KNN-57.32%, RF-93.97%	OASIS	Multi-Classification model achieves ordinary results
[10]	RF-97%	Day Care (Mayo)	RF couldn't recognize this case PSP
[11]	RF-80.1%, NB-75.8%	NACC	Inconsistencies in the data
[12]	2D-3D CNN's-96.80%	MNIST or ImageNet	Restrictied knowledge in identifying the parts of the brain affected by AD
[13]	SVM_ADNI-100%, SVM_OASIS-97%	ADNI & OASIS	Potential for improved early-stage AD prediction with advanced deep learning on combined datasets
[14]	SVM-90%, CNN-88%, LSTM-91%	ADNI	Challenges in data heterogeneity and model interpretability necessitate further exploration
[15]	RF-87%	OASIS	Advancement and broad improvements required
[16]	DT-82.82% RF-92.01%	ADNI	Medical experts don't trust ML decision without an accurate explanation
[17]	J48-96.92%, NB-76.92, SMO-87.70%	Kaggle	Sole reliance on CSF biomarkers ignores other factors influencing cognitive impairment
[18]	SVM-72.5%, RF-74%, ANN-77%	ADNI	Needs more data and exploring other ways to improve accuracy
[19]	SVM-79%, RF-83%, DT-81%, KNN-71%	ADNI	Large data is needed to validate the DL models
[20]	CNN:94.23%, SVM & MLP:97.47%	(BRFSS)	Interpretability Challenges & Limited dataset size
[21]	Mask R-CNN: 97.46%	ADNI	Small dataset, limited disease type, Single evaluation metric
[22]	Inception-ResNet-V2- 94.9%	ADNI, AIBL, MIRIAD, OASIS	Sole use of structural MRI data, reliance on ADNI database for labels
[23]	CNN-80%	Statista & OASIS	Diagnosis of mild cognitive impairment is difficult than diagnosing AD
[24]	RF-93.95%, SHAP-93.94%	ADNI, AIBL, MIRIAD, OASIS	Validation needed on diverse datasets for real-world clinical application

[25]	MiFi-90%	ADNI, OASIS, AIBL	Overfitting and, limited medical data
[26]	CNN-96.8%	ADNI	Dependency on 18FDG-PET images restrict applicability

III. Research Methodology

In our research methodology, we utilized CNN and RNN models for the detection of AD, each tailored to process distinct types of input data. The CNN model begins with the reception of medical imaging data, represented as 2D arrays, wherein convolutional layers extract spatial features via filters, capturing intricate patterns such as edges and textures. Following convolution, activation functions like ReLU introduce non-linearity, crucial for learning complex representations. Subsequent pooling layers down sample feature maps, reducing computational load while retaining essential information. Flattening transforms these maps into 1D vectors, inputted to fully connected layers for classification. In contrast, the RNN model operates on sequential clinical data. Its recurrent layers, comprising LSTM or GRU cells, sustain hidden states across time steps, capturing temporal dependencies crucial for understanding longitudinal patient data. The output layer, fed by the final hidden state, provides classification probabilities. This dual approach harnesses CNNs' proficiency in spatial feature extraction and RNNs' aptitude for temporal pattern recognition, offering a comprehensive analysis of diverse data modalities to enhance Alzheimer's disease detection accuracy. Algorithmic Steps involved in the process is described below as:

Start: This step is the beginning of the making of the machine learning model for Ad detection. It is the initial point where the process starts.

Data Input: In this step, the relevant data required for the model training is provided, in this dataset from different sources like Kaggle and OASIS is used for the training of the machine learning model.

Data Pre-processing: This step involves the preparation of the data that is obtained from Kaggle and OASIS for the machine learning model. Tasks such handling missing values, normalizing the images and data augmentation are performed to make sure the data is cleaned and suitable for training.

Model Building: In this step, the machine learning model is constructed, it involves the selection of appropriate model architecture, and the appropriate algorithm to be used, it is a crucial stage as determining the model and laying the foundation for the machine learning model, the choice of algorithm and model determines the performance of the machine learning model.

Model Evaluation and testing: Once the model is trained, it is tested against the dataset to assess its performance, evaluation parameters such as Accuracy, Precision are used to identify how well the model performs against the dataset provided, this step determines whether is precise or not.

End: This step marks the conclusion of the making of the machine learning model. It signifies the end of the process and the completion of the tasks shown in the workflow.

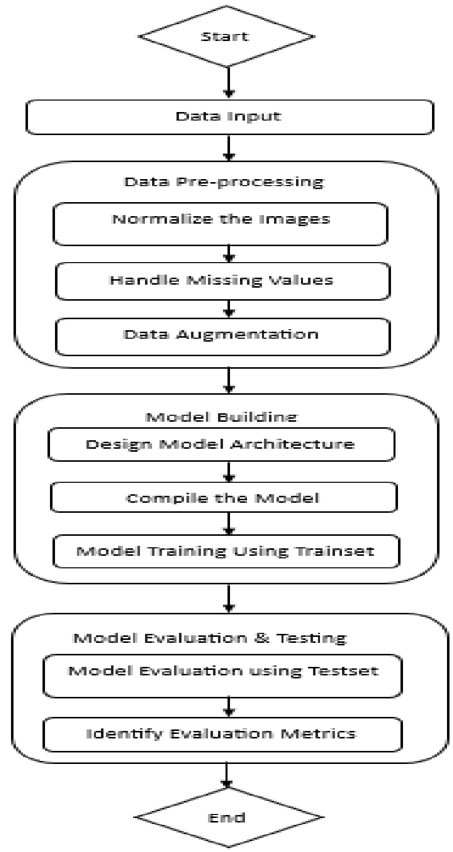

Fig. 1. Flow Chart of proposed Technique.

IV. Result and discussion

Classifying brain images is an essential part of medical imaging analysis that helps with neurological disorder diagnosis and treatment. CNNs and RNNs were used in this study to categorize brain pictures and offer accuracy. Two distinct datasets from various sources have been used. They both come from OASIS and Kaggle, respectively. Pituitary, Notumor, Meningioma, and Glioma are the four categories into which Kaggle divides its image collection. Additionally, four categories listed as Non-Demented, Very Mild Dementia, Mild Dementia, and Moderate Dementia—are applied to the brain scans in the OASIS dataset. NumPy, Pandas, Keras, OS, matplotlib, seaborn, sklearn, TensorFlow, and PIL are some of the libraries we imported to assist us develop our model on AD Detection Model. The Kaggle dataset has been splitted into 4417 training photos, 632 validation images, and 1262 testing images. Additionally, 391 photos are used for testing and 1561 images are used for training in the OASIS dataset. In the Kaggle dataset, the data has already been divided into two distinct files called training and testing. And in the other model, we used the train_test_split function from the library that we initially loaded to separate the data into training and testing. To ensure that the input and dimensions of all the samples were consistent, each image was scaled to 128 by 128 pixels. One-hot encoding was used to represent the categorical labels once the data was loaded and preprocessed, which included resizing and transforming the photos into NumPy-arrays. The splitting of the data was performed using an 80-20 ratio. 20% of the data was used for testing or evaluation purposes.

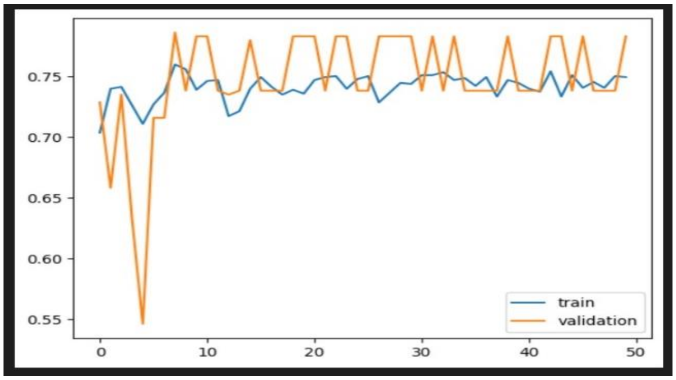

Fig. 2. Accuracy Graph of RNN- 73.15% (OASIS Dataset)

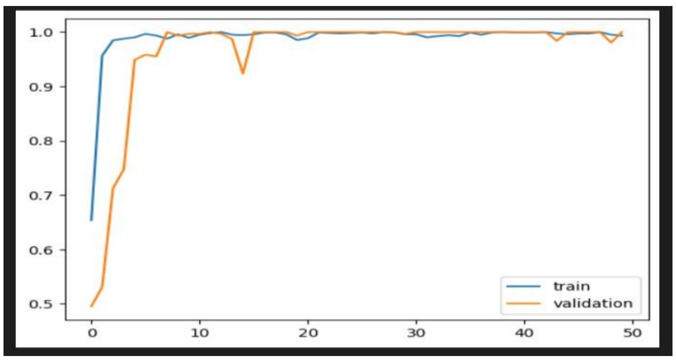

Fig. 3. Accuracy Graph of CNN- 100% (OASIS Dataset)

The CNN design is sequential and consists of several convolutional layers, followed by dense blocks, max-pooling, dropout, and batch normalization. On the other hand, the RNN model was created by changing the CNN architecture, using Simple RNN layers and then dense layers. To capture the sequential information included in the data, an LSTM layer was added to one of the models' places of the CNN's final layer. The performance of both models was assessed on different test sets after they had been trained on preprocessed image data. Throughout training, the CNN model performed admirably, obtaining high accuracy and minimal loss on the training set. Furthermore, measurements showing promising findings for successful brain image classification included AUC, precision, and recall. The model's capacity for generalization was further supported by validation results, which showed epoch-by-epoch convergence of training and validation metrics. Test set evaluation yielded real-world performance insights and demonstrated CNN's accuracy in classifying brain images into several categories. To avoid overfitting and guarantee ideal model performance, early halting was used.

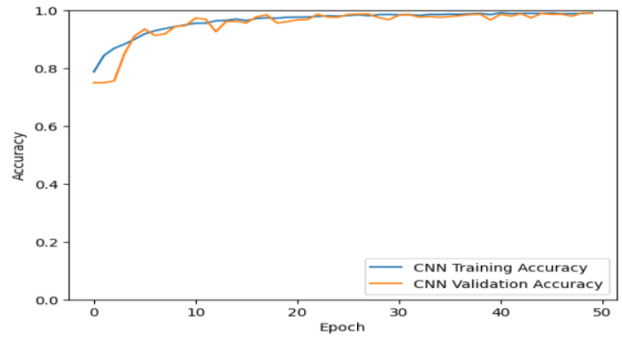

Fig. 4. Accuracy Graph of CNN- 73.15% (Kaggle Dataset)

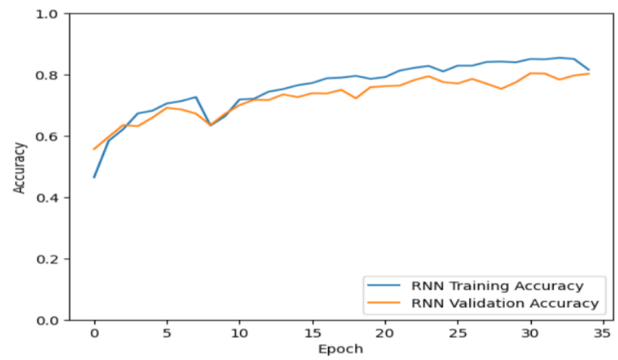

Fig. 5. Accuracy Graph of RNN- 80.27% (Kaggle Dataset)

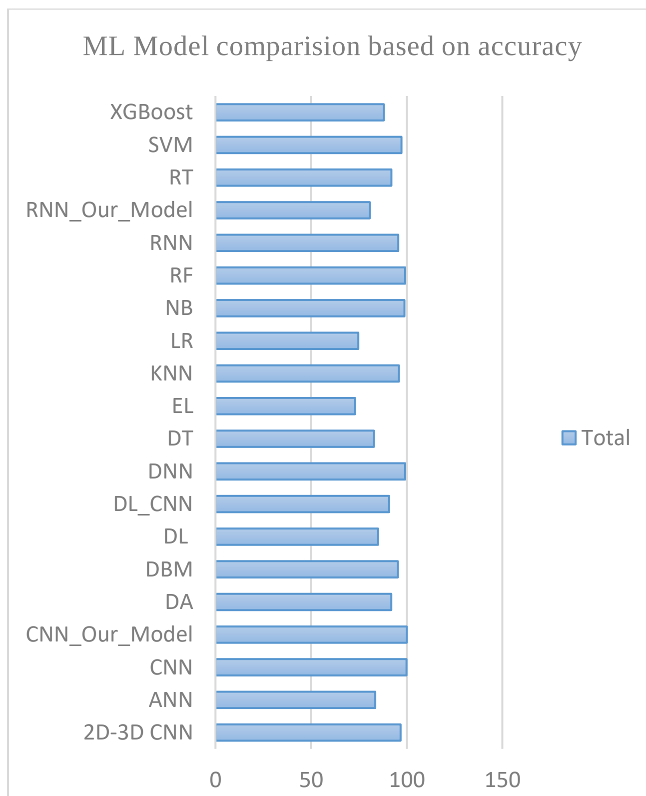

Fig. 6. Perfromance comparision of proposed model with existing models

The RNN model, on the other hand, treated each row of pixels as a sequence and took advantage of the sequential facts present in the image data. In terms of brain image classification, RNN outperformed CNN despite having a simpler design. To avoid overfitting, early halting was used during the model's compilation and training process, which followed CNN setups. The RNN's learning process was monitored via training and validation metrics, which demonstrated gains in accuracy and loss over epochs. The evaluation of the test set demonstrated how well the RNN complemented the CNN's performance in classification by using sequential patterns. Plotting the RNN model's training history allowed for the visualization of its learning process and revealed convergence behavior that was comparable to that of the CNN. Competitive performance was revealed by evaluation on the test set, proving the value of using sequential information for brain image categorization.

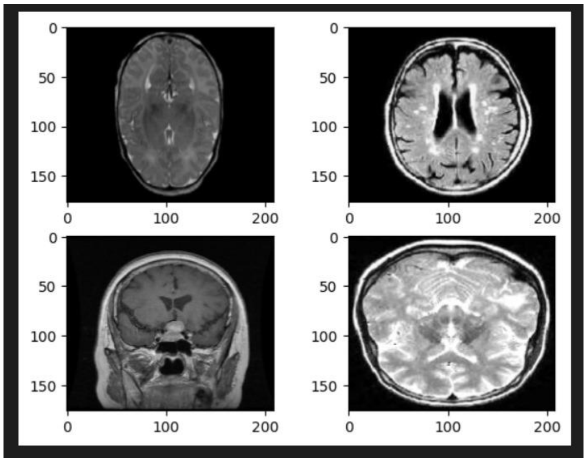

Fig. 7. Brain Images with AD

Fig. 7,8,9,10 represents the view of brain with the help of images from various directions captured with the implemented model.

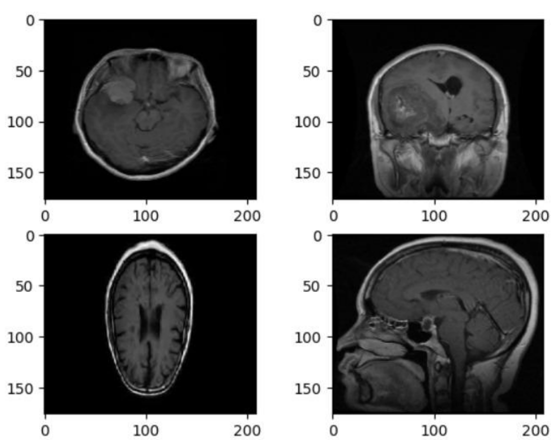

Fig. 8. Brain Images having AD

As a result of our research, CNNs and RNNs are efficient in classifying brain images into several groups. On the OASIS and Kaggle datasets, CNN demonstrated exceptional accuracy of 100% and 97.33%, respectively, whereas the RNN demonstrated marginally lower accuracy of 73.15% and 80.67% on the same datasets.

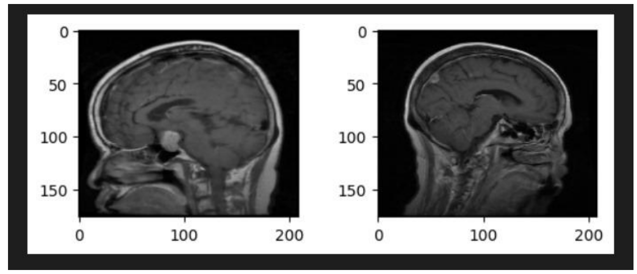

Fig. 9. Some Brain Images of Left and Right View

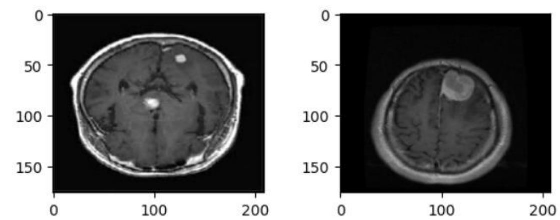

Fig. 10. Some Brain Images of Top View

This difference highlights how each architecture is better at different tasks; CNNs are better at capturing spatial information, while RNNs are better at capturing temporal dependencies and sequential patterns. Our results highlight how important it is to choose the right architecture depending on the details of the task and the properties of the data. The future holds potential for significantly improving classification accuracy and clinical relevance using larger datasets, improved model architectures, and investigation of sophisticated data augmentation approaches. All things considered, our study demonstrates the ability of deep learning models in precisely categorizing brain images and emphasizes the necessity of ongoing research and development to successfully handle clinical issues.

V. Conclusion

The study demonstrates the effectiveness of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) in categorizing brain images. CNNs excel in capturing spatial details, while RNNs are adept at understanding temporal relationships and sequential patterns. CNNs achieved high accuracy rates of 100% and 97.33% on the OASIS and Kaggle datasets, while RNNs achieved slightly lower accuracies of 73.15% and 80.67%. The study suggests that future advancements in classification accuracy and clinical relevance can be achieved through larger datasets, improved model designs, and sophisticated data augmentation strategies. The findings highlight the need for research and development to address clinical challenges and suggest promising avenues for enhancing classification accuracy and clinical applicability. These efforts are crucial in medical imaging analysis, leading to more accurate diagnoses and improved patient care.

References

[1] M. Bari Antor *et al.*, "A Comparative Analysis of Machine Learning Algorithms to Predict Alzheimer's Disease," *J. Healthc. Eng.*, vol. 2021, 2021, doi: 10.1155/2021/9917919.

[2] S. Dogan *et al.*, "Primate brain pattern-based automated Alzheimer's disease detection model using EEG signals," *Cogn. Neurodyn.*, vol. 17, no. 3, pp. 647–659, Jun. 2023, doi: 10.1007/s11571-022-09859-2.

[3] C. H. Chang, C. H. Lin, and H. Y. Lane, "Machine learning and novel biomarkers for the diagnosis of alzheimer's disease," *International Journal of Molecular Sciences*, vol. 22, no. 5. MDPI AG, pp. 1–12, Mar. 01, 2021. doi: 10.3390/ijms22052761.

[4] A. Chakravarthy, B. S. Panda, and S. K. Nayak, "Review and Comparison for Alzheimer's Disease Detection with Machine Learning Techniques 1," vol. 27, no. 4, 2023, doi: 10.5123/inj.2023.4.inj42.

[5] G. Battineni, N. Chintalapudi, F. Amenta, and E. Traini, "A comprehensive machine-learning model applied to magnetic resonance imaging (MRI) to predict Alzheimer's disease (ad) in older subjects," *J. Clin. Med.*, vol. 9, no. 7, pp. 1–14, Jul. 2020, doi: 10.3390/jcm9072146.

[6] J. Bin Bae *et al.*, "Identification of Alzheimer's disease using a convolutional neural network model based on T1-weighted magnetic resonance imaging," *Sci. Rep.*, vol. 10, no. 1, Dec. 2020, doi: 10.1038/s41598-020-79243-9.

[7] X. Tang and J. Liu, "Comparing different algorithms for the course of alzheimer's disease using machine learning," *Ann. Palliat. Med.*, vol. 10, no. 9, pp. 9715–9724, Sep. 2021, doi: 10.21037/apm-21-2013.

[8] R. Kumari, A. Nigam, and S. Pushkar, "Machine learning technique for early detection of Alzheimer's disease," *Microsyst. Technol.*, vol. 26, no. 12, pp. 3935–3944, Dec. 2020, doi: 10.1007/s00542-020-04888-5.

[9] 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," *Multimed. Tools Appl.*, vol. 80, no. 28–29, pp. 35789–35807, Nov. 2021, doi: 10.1007/s11042-020-09087-y.

[10] S. Koga, A. Ikeda, and D. W. Dickson, "Deep learning-based model for diagnosing Alzheimer's disease and tauopathies," *Neuropathol. Appl. Neurobiol.*, vol. 48, no. 1, Feb. 2022, doi: 10.1111/nan.12759.

[11] N. An, H. Ding, J. Yang, R. Au, and T. F. A. Ang, "Deep ensemble learning for Alzheimer's disease classification," *J. Biomed. Inform.*, vol. 105, May 2020, doi: 10.1016/j.jbi.2020.103411.

[12] A. Ebrahimi, S. Luo, and for the A. Disease Neuroimaging Initiative, "Convolutional neural networks for Alzheimer's disease detection on MRI images," *J. Med. Imaging*, vol. 8, no. 02, Apr. 2021, doi: 10.1117/1.jmi.8.2.024503.

[13] A. W. Salehi, P. Baglat, and G. Gupta, "Alzheimer's Disease Diagnosis using Deep Learning Techniques," *Int. J. Eng. Adv. Technol.*, vol. 9, no. 3, pp. 874–880, Feb. 2020, doi: 10.35940/ijeat.C5345.029320.

[14] B. Yadav Kasula, "International Journal of Sustainable Development in Computing Science A Machine Learning Approach for Differential Diagnosis and Prognostic Prediction in Alzheimer's Disease JOURNAL I N F O." [Online]. Available: www.ijsdcs.com

[15] A. Khan and S. Zubair, "An Improved Multi-Modal based Machine Learning Approach for the Prognosis of Alzheimer's disease," *J. King Saud Univ. - Comput. Inf. Sci.*, vol. 34, no. 6, pp. 2688–2706, Jun. 2022, doi: 10.1016/j.jksuci.2020.04.004.

[16] S. El-Sappagh, H. Saleh, F. Ali, E. Amer, and T. Abuhmed, "Two-stage deep learning model for Alzheimer's disease detection and prediction of the mild cognitive impairment time," *Neural Comput. Appl.*, vol. 34, no. 17, pp. 14487–14509, Sep. 2022, doi: 10.1007/s00521-022-07263-9.

[17] S. Asif Hassan and T. Khan, "A Machine Learning Model to Predict the Onset of Alzheimer Disease using Potential Cerebrospinal Fluid (CSF) Biomarkers," 2017. [Online]. Available: www.ijacsa.thesai.org

[18] E. Lella *et al.*, "Machine learning and DWI brain communicability networks for Alzheimer's disease detection," *Appl. Sci.*, vol. 10, no. 3, Feb. 2020, doi: 10.3390/app10030934.

[19] J. Venugopalan, L. Tong, H. R. Hassanzadeh, and M. D. Wang, "Multimodal deep learning models for early detection of Alzheimer's disease stage," *Sci. Rep.*, vol. 11, no. 1, Dec. 2021, doi: 10.1038/s41598-020-74399-w.

[20] K. N. Rao, B. R. Gandhi, M. V. Rao, S. Javvadi, S. S. Vellela, and S. Khader Basha, "Prediction and Classification of Alzheimer's Disease using Machine Learning Techniques in 3D MR Images," *Int. Conf. Sustain. Comput. Smart Syst. ICSCSS 2023 - Proc.*, no. Icscss, pp. 85–90, 2023, doi: 10.1109/ICSCSS57650.2023.10169550.

[21] M. R-cnn, "INTELLIGENT SYSTEMS AND APPLICATIONS IN Brain MRI Image Analysis for Alzheimer ' s Disease Diagnosis Using," vol. 12, pp. 137–149, 2024.

[22] B. Lu *et al.*, "A practical Alzheimer's disease classifier via brain imaging-based deep learning on 85,721 samples," *J. Big Data*, vol. 9, no. 1, Dec. 2022, doi: 10.1186/s40537-022-00650-y.

[23] A. Yiğit and Z. Işik, "Applying deep learning models to structural MRI for stage prediction of Alzheimer's disease," *Turkish J. Electr. Eng. Comput. Sci.*, vol. 28, no. 1, pp. 196–210, 2020, doi: 10.3906/elk-1904-172.

[24] S. El-Sappagh, J. M. Alonso, S. M. R. Islam, A. M. Sultan, and K. S. Kwak, "A multilayer multimodal detection and prediction model based on explainable artificial intelligence for Alzheimer's disease," *Sci. Rep.*, vol. 11, no. 1, Dec. 2021, doi: 10.1038/s41598-021-82098-3.

[25] S. Gao and D. Lima, "A review of the application of deep learning in the detection of Alzheimer's disease," *International Journal of Cognitive Computing in Engineering*, vol. 3. KeAi Communications Co., pp. 1–8, Jun. 01, 2022. doi: 10.1016/j.ijcce.2021.12.002.

[26] A. A, P. M, M. Hamdi, S. Bourouis, K. Rastislav, and F. Mohmed, "Evaluation of Neuro Images for the Diagnosis of Alzheimer's Disease Using Deep Learning Neural Network," *Front. public Heal.*, vol. 10, p. 834032, 2022, doi: 10.3389/fpubh.2022.834032.