International Journal of Informatics and Communication Technology (IJ-ICT)
Vol. 13, No. 2, August 2024, pp. 206~213
ISSN: 2252-8776, DOI: 10.11591/ijict.v13i2.p206-213

Alzheimer's disease diagnosis using convolutional neural networks model

Potnuru Samanvi[1], Shruti Agrawal[1], Soubhagya Ranjan Mallick[2], Rakesh Kumar Lenka[3], Shantilata Palei[1], Debani Prasad Mishra[4], Surender Reddy Salkuti[5]
[1]Department of Computer Science and Engineering, IIIT Bhubaneswar, Bhubaneswar, India
[2]School of Technology, Woxsen University, Hyderabad, India
[3]Department of Computer Science, Central University of Odisha, Odisha, India
[4]Department of Electrical and Electronics Engineering, IIIT Bhubaneswar, Bhubaneswar, India
[5]Department of Railroad and Electrical Engineering, Woosong University, Daejeon, Republic of Korea

Article Info

Article history:

Received Feb 12, 2024
Revised Apr 25, 2024
Accepted May 12, 2024

Keywords:

Alzheimer
CNN
Deep learning
Disease diagnosis
Prediction

ABSTRACT

The global healthcare system and related fields are experiencing extensive transformations, taking inspiration from past trends to plan for a technologically advanced society. Neurodegenerative diseases are among the illnesses that are hardest to treat. Alzheimer's disease is one of these conditions and is one of the leading causes of dementia. Due to the lack of permanent treatment and the complexity of managing symptoms as the severity grows, it is crucial to catch Alzheimer's disease early. The objective of this study was to develop a convolutional neural network (CNN)-based model to diagnose early-stage Alzheimer's disease more accurately and with less data loss than methods previously discovered. CNN, is adept at processing and recognising images and has been employed in various diagnostic tools and research in the healthcare sector, showing limitless potential. Convolutional, pooling and fully linked layers are the common layers that make up a CNN. In this paper, five CNN modelswere randomly chosen (ResNet, DenseNet, MobileNet, Inception, and Xception) and were trained. ResNet performed the best and was chosen to undergo additional modifications to improve accuracy to 95.5%. This was a remarkable achievement that made us hopeful for the performance of this model in larger datasets as well as other disease detection.

Corresponding Author:

Surender Reddy Salkuti
Department of Railroad and Electrical Engineering, Woosong University
Jayang-Dong, Dong-Gu, Daejeon - 34606, Republic of Korea
Email: surender@wsu.ac.kr

1. INTRODUCTION

Alzheimer's disease is a neurological condition that impairs memory and cognitive function over time [1]. It is the most frequent cause of dementia, accounting for 60-70% of all cases. It is a progressive and irreversible brain disorder that impairs cognitive functioning and contributes to memory loss, eventually making it difficult for a person to carry out even the most basic daily tasks. In 1906, Dr. Alois Alzheimer noticed changes in the brain tissue of a dead woman, where he found many abnormal clumps and tangled bundles of fibres. Her symptoms before death included unstable behaviour, memory loss, and language difficulties. The primary characteristics of Alzheimer's are still found to be these observations. The rise in long-term care expenditures coupled with the increasing frequency of this neurodegenerative ailment, which has no known cure, emphasizes the urgent need for novel ways to early detection and management of the disease.

Convolutional neural networks (CNNs) are one promising strategy for disease diagnosis. CNNs [2] is a deep learning algorithm well-suited for image analysis. Figure 1 shows the feature extraction process in a basic CNN model. CNNs can recognise patterns that may not be immediately obvious to human observers when applied to medical imaging, such as brain magnetic resonance images (MRI) scans, and can identify subtle abnormalities and detect specific biomarkers associated with a disease, enabling more precise and efficient diagnoses while also assisting medical professionals in understanding disease in greater depth. Although CNNs have the potential to diagnose Alzheimer's disease, they should be used in conjunction with professional medical judgment rather than as a substitute. Together, CNN algorithms and human clinicians may produce more thorough and precise diagnoses, ultimately improving patient outcomes and the quality of the healthcare system. By making early diagnosis more accessible and affordable, CNNs could help to reduce the burden of Alzheimer's disease on individuals, families, and society as a whole.

The first step in doing research is to go through previously published works to determine the lacuna. During the early reading of research papers in the healthcare sector, there was a distinct lack of publications related to Alzheimer's disease. As Alzheimer's is a disease with no known cure, it becomes all the more important to detect it as early as possible so that the progress of symptoms can be regulated. While machine learning has been extensively used for detecting and diagnosing diseases, and to provide better assistance to medical professionals in treating patients, the models that utilized the more complex deep learning technique were scarce. This drove us to develop this model in hopes of providing further assistance. The models that could currently diagnose Alzheimer's disease either have poor accuracy or are overfit to their datasets. This study aims to improve diagnostic precision and reduce the danger of overfitting deep learning models. To aid in the early diagnosis of Alzheimer's, the dataset used includes samples of non-demented and very mildly demented MRI scans in addition to mild and moderate demented ones. The main goal of this study is to accurately and promptly diagnose Alzheimer's in order to promote the patient's recovery.

This paper presents several key contributions to the final model proposal, including developing a modified CNN model, collecting a dataset of brain MRI scans, and evaluating the model on the dataset.

- Five randomly chosen CNN models, namely ResNet, DenseNet, MobileNet, Inception, and Xception, were trained using supervised learning methods, and the results were analysed.
- Additional layers like dropout and dense(fully connected) layers were added to the best-performing model to increase the accuracy of the diagnosis.
- Finally, the model was tested on test data to determine its performance, and the confusion matrices, reciever operating characteristic curve (ROC), and precision-recall graphs were plotted.

With the best accuracy of 90.789% using KNN, Shah *et al.* [3] model proposes employing 14 attributes to predict cardiac illnesses from the Cleveland database of the UCI repository. By comparing five models utilizing factors including recall, accuracy, precision, and F-score, Kavitha *et al.* [4] proposed the best functioning model for diagnosing early-stage Alzheimer's patients using a dataset available on OASIS and Kaggle. Shamrat *et al.* [5] suggest a machine learning based forecasting method using the Wisconsin breast cancer dataset. The support vector machines (SVM) achieved the highest prediction accuracy of the six supervised classification algorithms in the paper, with 97.07%. Haruna *et al.* [6] 2023 introduced a new technique that enhanced COVID-19 classification from X-ray radiograph images by combining VGG19 and ResNet50V2 architectures. With an accuracy rate of 87.48%, random forest (RF) outperformed the other models in Wu *et al.* [7] study of four classification models for the prediction of fatty liver disease. Scholar [8] use machine learning algorithms like decision trees and Naive Bayes to identify kidney diseases. A system for the early diagnosis of chronic renal illness using data from the UCI machine learning repository was proposed by Reshma *et al.* [9]. Decision tree and Naive Bayes are two machine learning models trained to predict the disease, and the end results reveal that the decision tree has better outcomes (99.25%). Four different machine learning techniques are used by Krishnamoorthi *et al.* [10] to research healthcare predictive analytics in diabetes. The suggested approach provides 83% accuracy with a low error rate, demonstrating that logistics regression outperformed other models. Diab *et al.* [11] in 2022 introduced an automated technique using deep learning for accurate prediction and diagnosis of melanoma utilizing a computer-aided diagnosis system with CNN-based feature extraction. They achieved high accuracy rates on different datasets. A thorough assessment of machine learning based automated diagnosis systems is carried out by Javeed *et al.* [12] utilizing a variety of datasets, including pictures and speech data. The study discovered that approaches relying on image data modality performed better compared to other machine learning techniques. The review paper by Zhao *et al.* [13] reviews conventional machine learning methods like SVM, RF, CNN, and others for classifying and predicting Alzheimer's disease using MRI, discussing challenges, trade-offs, and suggestions for preprocessing and technique selection. It also explores various feature extractors and input forms for CNNs in depth. In 2023, a study by Pacal *et al.* [14] explored traditional machine learning techniques for Alzheimer's classification and prediction using MRI data, including transformers, autoencoders, deep learning, RF, SVM, and CNN. Erdaş *et al.* [15] focused on deep learning techniques for the early detection of colon cancer, aiming to put advancements into perspective. A study by Jyotiyana and Kesswani [16] developed a deep-learning model using gait features collected by GRF sensors to detect and assess the severity of neurodegenerative diseases. In 2021, Miao and Miao [17] highlighted the role of deep learning in addressing brain problems and its potential for more effective and efficient patient treatment.

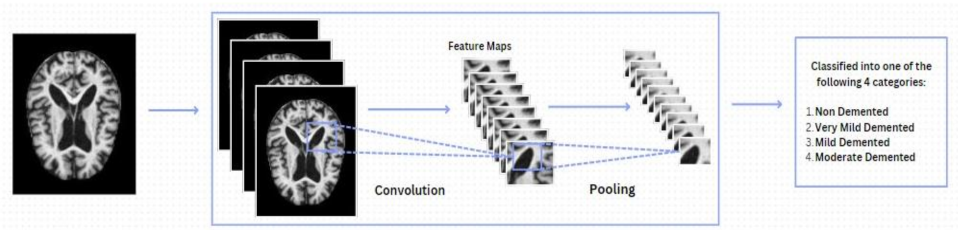

Figure 1. Feature extraction in CNN model

2. METHOD

The data utilized in the research are MRI scans downloaded from Kaggle. This dataset was formed after gathering data from various legitimate sources and was then accurately labelled [18], [19]. They are divided into four classes: non-demented, very mild demented, mild demented, and moderately demented scans of patients. A total of 6,400 scans, each segregated into the severity of Alzheimer's, were availed. The four MRI scans given in Figure 2 are the samples from the dataset taken showing the non-demented, very mild, mild, and moderately demented brain scans chronologically.

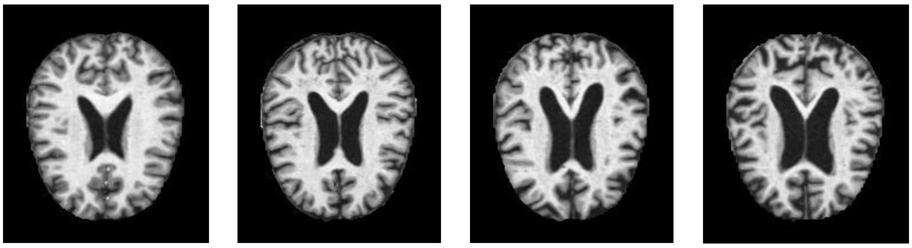

Figure 2. Sample brain MRI scan images

The brain MRI scan images were preprocessed according to the requirements. First, the pixels in the images were rescaled by a factor of 1,255. The brightness range was set to ±20%, and the zoom range was set to 99% to 101%. Since all 4 classes of images did not contain a similar number of images in the used dataset, data augmentation was performed to balance out the classes using the synthetic minority over-sampling technique [18]. After using SMOTE, the dataset was divided into training and testing datasets, with 80% as training data and 20% as testing data [20]. Then the training data was split into two parts, with 80% as the training dataset and 20% as the validation dataset, which was then used for training the models [21], [22]. Figure 3 can be observed to understand the steps involved in making the model. After the pre-processing of the dataset, 5 different CNN models, i.e., InceptionV3, DenseNet121, ResNet50V2, Xception, and MobileNetV2, were chosen for the purpose of finding the best-performing algorithm for diagnosing Alzheimer's. All the chosen models were trained using the same method, and their results were compared. After analysing the results, it was found that ResNet50V2 had the best performance among all five models and was chosen as the base model. Additional dropout layers, batch normalisation, and dense (fully connected) layers were included to improve its performance.

This paper considered several hyperparameters to optimise the model's performance. Firstly, the learning rate was set at 0.001 to control the step size at which the weights of a model change during training. The optimiser [23] used was initially named "RMSProp," but it was changed to "Adam" to boost the performance of the model. Regularisation techniques [24] were employed to prevent the model's overfitting, including using L2 kernel regularisers at all dense (or fully connected) layers. It introduces a penalty term to loss function based on the model's weights and encourages smaller weights. To prevent over-reliance on any specific feature, a dropout [25] set was introduced at 0.5 in between layers, which randomly shuts down a fraction of neurons. Batch normalisation [26] was applied between layers of the CNN model so that the input data for the next layer always remained within a specific range. Additionally, the 'ReLU' (rectified linear unit) activation function [27] was used for all fully connected layers barring the last one where the 'Softmax' activation function was availed, which helped introduce non-linearity to the network.

After making all the necessary modifications to achieve the best performance, the pre-processed data was fed into the final CNN model, which was created using ResNet50V2 as the base model. After the convergence of the CNN model, the weights of the last 28 layers of the pre-trained model were unfrozen, and the model was re-trained. This model was able to achieve an overall accuracy of 95.5%.

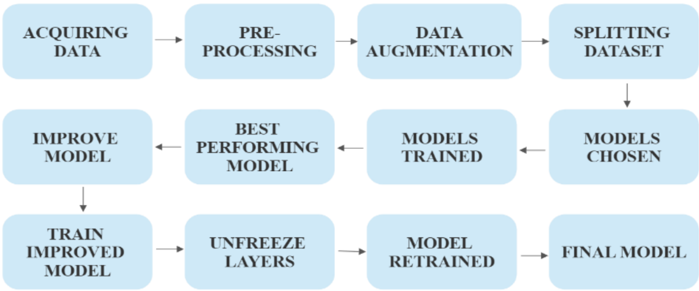

Figure 3. Flowchart of the final model

3. RESULTS AND DISCUSSION

Table 1 presents the accuracy and loss for all models proposed in this paper. Based on Table 1, it becomes evident that the ResNet50V2 model outperformed the others, achieving an accuracy of 87.84%. Following closely behind was the MobileNetV2 model, with an accuracy of 87.32%. Regarding loss, ResNet50V2 exhibited the lowest value compared to the other models. These promising results solidified the selection of ResNet50V2 as the base model for further improvements.

Table 1. Accuracy and loss for all models

Models	Accuracy in (%)	Loss
ResNet50V2	87.84	0.32
DenseNet121	84.40	0.40
InceptionV3	85.41	0.39
Xception	84.95	0.39
MobileNetV2	87.32	0.33
Final model	95.53	0.29

The formulas for accuracy and loss used are given in (1) and (2), respectively [28].

$$Accuracy = \frac{Number\ of\ correctly\ predicted\ samples}{Total\ number\ of\ samples} \tag{1}$$

$$Loss = -\Sigma(true\ distribution\ + \log(predicted\ distribution)) \tag{2}$$

Afterwards, additional layers were incorporated into the ResNet50V2 base model, and extensive hyperparameter tuning [29] was performed. These efforts resulted in the development of a highly optimised final model. The rigorous optimisation process significantly enhanced the model's performance, achieving an impressive accuracy of 95.53%. This significant improvement demonstrates the effectiveness of the applied techniques in enhancing the model's performance from its initial state. The combination of architectural enhancements and meticulous parameter adjustments resulted in a final model that excelled in making accurate predictions.

The performance evaluation and comparison of the different models involved the utilisation of multiple key evaluation metrics. Accuracy served as a measure of overall correctness, accompanied by categorical cross-entropy loss, which gauged the dissimilarity between predicted probabilities and accurate class labels, thus aiding the training process. Precision and recall were employed to assess the performance of each individual class. Additionally, the ROC curve provided insights into the model's overall performance.

To further analyse and understand the model's predictions, confusion matrices were generated using the matplotlib [26] library, effectively summarising the predicted and true class labels and offering valuable performance insights. Figures 4 and 5 present the confusion matrices for the basic ResNet50V2 and the improved final model.

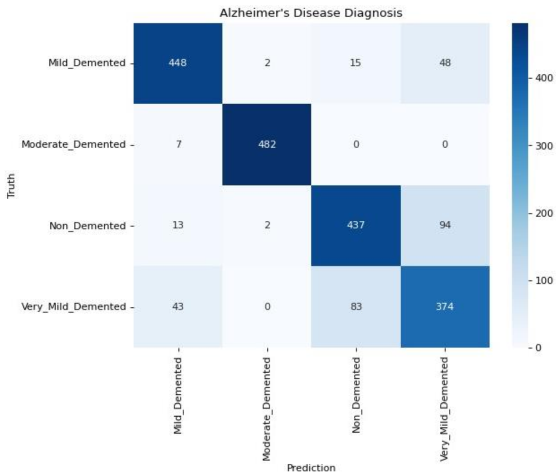

Figure 4. Confusion matrix for basic ResNet50V2

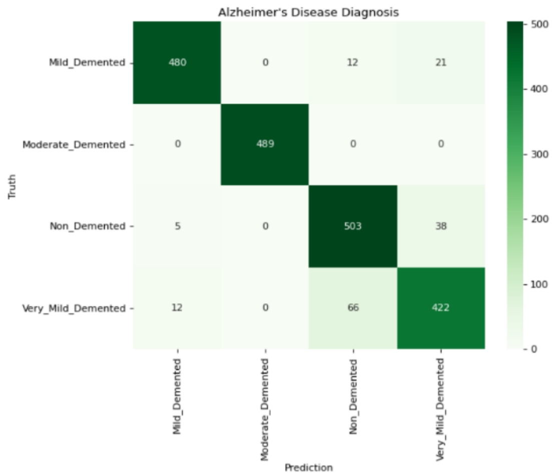

Figure 5. Confusion matrix for final model

The final model demonstrates the highest accuracy and consistent performance across the different classes. The ROC curve and precision-recall graph of the final model given in Figures 6 and 7 further shows the model's efficiency. Moreover, a comparison of the performance of the five initial models allows us to conclude that ResNet50V2 exhibited the best overall performance, justifying its selection as the base model.

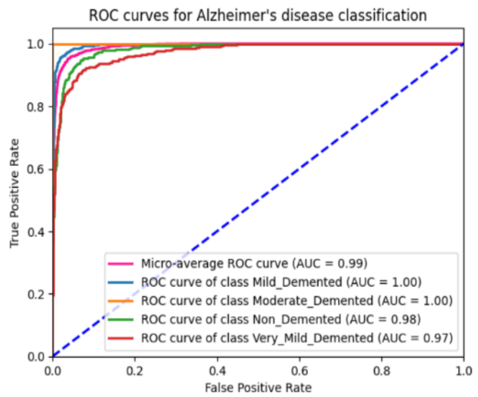

Figure 6. ROC curve of final model

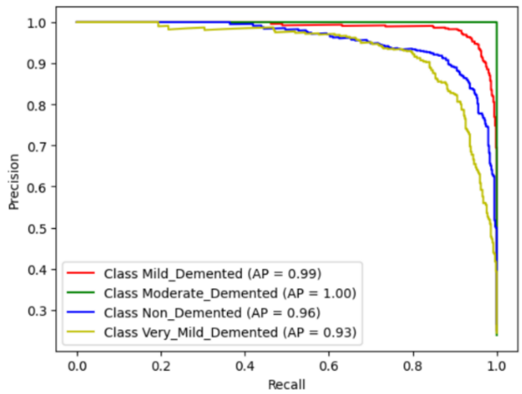

Figure 7. Precision-recall graph of final model

Remarkable improvements were achieved by implementing the aforementioned methods to enhance the ResNet50V2 model. The final CNN model attained an impressive accuracy of 95.53% and a loss of 0.29. The ROC and precision-recall curves can be examined to gain further insights into the final model's performance, providing valuable information about its predictive capabilities and class-specific performance.

4. CONCLUSION

Alzheimer's is a cumulative neurological disorder that threatens human life. This study aims to build an efficient model for diagnosing Alzheimer's to assist medical professionals. With no known cure for Alzheimer's, accurate prediction can nonetheless offer useful information for individualised therapies and a clearer understanding of disease progression. Cross-validating a number of CNN models, namely ResNet50V2, DenseNet121, InceptionV3, Xception, and MobileNetV2, the one that performed the best was improved to make precise predictions. ResNet, which showed the best performance, was chosen as the base model for further modifications. The paper optimised the model's performance using various hyperparameters such as a learning rate of 0.001, changing the optimiser to 'Adam', L2 kernel regularisers, dropout of 0.5, batch normalisation, and 'relu' and 'Softmax' activations for introducing non-linearity. The high accuracy rate of the proposed model trained to the brain MRI images is remarkable. The integration of several data sources will be the future path of this research, with the goal of increasing the model's diagnostic precision. This paper presents this research in hopes that it will be helpful in further studies and help people receive early care and live better lives.

ACKNOWLEDGEMENTS

This research work was supported by "Woosong University's Academic Research Funding - 2024".

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BIOGRAPHIES OF AUTHORS

Potnuru Samanvi is an ambitious student pursuing a Bachelor of Technology degree in Computer Science and Engineering at the International Institute of Information Technology, Bhubaneswar. Their research interests focus on applying deep learning and machine learning to fields such as computer vision, natural language processing, and data analytics. She has strong programming skills and a solid foundation in machine-learning algorithms and techniques. They are eager to collaborate with researchers and industry professionals to develop practical solutions and make a positive impact using deep learning and machine learning technologies. She can be contacted at email: b119039@iiit-bh.ac.in.

Shruti Agrawal is a bright student pursuing her Bachelor's in technology from the International Institute of Information Technology in the field of Computer Science and Engineering. Her research interests include machine learning, natural language processing, and computer vision. She is particularly invested in using machine learning to solve real-world problems and technology to improve people's lives. She believes machine learning has a huge untapped potential to revolutionise how we diagnose and treat diseases. She is enthusiastic about future collaborations and committed to making her research accessible to the public. She can be contacted at email: b119053@iiit-bh.ac.in.

Soubhagya Ranjan Mallick is pursuing his Ph.D. Computer Science and Engineering degree at IIIT Bhubaneswar, Odisha, India. He works as an Assistant Professor in the School of Technology, Woxsen University, Hyderabad, Telangana, India. He has more than 13 years of experience in teaching and research. His research interests include IoT, blockchain, cryptography, edge computing, fog computing, and cloud computing. He can be contacted at email: soubhagya.mallick@woxsen.edu.in.

Rakesh Kumar Lenka is working as an Associate Professor in the Department of Computer Science, Central University of Odisha. He has published over 60 research articles in reputed journals and conference proceedings. His research interests include Green IoT, fog/mist computing, model checking, blockchain technology, recommendation systems, geographical information systems, and DFA-based pattern matching. He is a Professional Member of the CSI and the International Association of Engineers (IAENG). He has served as a reviewer for various reputed international journals and conferences. He can be contacted at email: rklenka@cuo.ac.in.

Shantilata Palei born and raised in Odisha, completed her master of technology in Computer science and engineering branch and currently pursuing Ph.D. in computer science and engineering at the International Institute of Information Technology. Her research focuses on the integration of machine learning with blockchain. She is particularly intrigued by applying machine learning algorithms in large-scale data processing, aiming to develop novel techniques with blockchain technologies. Her work holds great promise for improving decision-making processes and optimizing various areas of smart cities. She can be contacted at email: c122011@iiit-bh.ac.in.

Debani Prasad Mishra received the B.Tech. in electrical engineering from the Biju Patnaik University of Technology, Odisha, India, in 2006 and the M.Tech. in power systems from IIT, Delhi, India in 2010. He has been awarded the Ph.D. degree in power systems from Veer Surendra Sai University of Technology, Odisha, India, in 2019. He is currently serving as Assistant Professor in the Department of Electrical Engineering, International Institute of Information Technology Bhubaneswar, Odisha. His research interests include soft computing techniques application in power system, signal processing, and power quality. He can be contacted at email: debani@iiit-bh.ac.in.

Surender Reddy Salkuti received the Ph.D. degree in electrical engineering from the Indian Institute of Technology, New Delhi, India, in 2013. He was a Postdoctoral Researcher with Howard University, Washington, DC, USA, from 2013 to 2014. He is currently an Associate Professor with the Department of Railroad and Electrical Engineering, Woosong University, Daejeon, South Korea. His current research interests include market clearing, including renewable energy sources, demand response, smart grid development with integration of wind and solar photovoltaic energy sources. He can be contacted at email: surender@wsu.ac.kr.