Alzheimer’s disease diagnosis using convolutional neural networks model

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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 recognizing 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 models were 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.

Keywords: Alzheimer, CNN, Deep learning, Disease diagnosis, Prediction

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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.

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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, receiver 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 Naïve 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 Naïve 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 logistic 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...

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 1. Feature extraction in CNN model

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%.

![Diagram](image)

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>
<thead>
<tr>
<th>Models</th>
<th>Accuracy in (%)</th>
<th>Loss</th>
</tr>
</thead>
<tbody>
<tr>
<td>ResNet50V2</td>
<td>87.84</td>
<td>0.32</td>
</tr>
<tr>
<td>DenseNet121</td>
<td>84.40</td>
<td>0.40</td>
</tr>
<tr>
<td>InceptionV3</td>
<td>85.41</td>
<td>0.39</td>
</tr>
<tr>
<td>Xception</td>
<td>84.95</td>
<td>0.39</td>
</tr>
<tr>
<td>MobileNetV2</td>
<td>87.32</td>
<td>0.33</td>
</tr>
<tr>
<td>Final model</td>
<td>95.53</td>
<td>0.29</td>
</tr>
</tbody>
</table>

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

\[
\text{Accuracy} = \frac{\text{Number of correctly predicted samples}}{\text{Total number of samples}} \tag{1}
\]

\[
\text{Loss} = -\sum (\text{true distribution} + \log(\text{predicted distribution})) \tag{2}
\]

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](image)

![Figure 5. Confusion matrix for final model](image)

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 show 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](image)

![Figure 7. Precision-recall graph of final model](image)

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
clarity 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.

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REFERENCES


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