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Early Detection of Alzheimer's Disease Using Deep Learning on MRI Images

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KEYWORDS

Alzheimer's Disease, MRI, OASIS Dataset, Convolutional Neural Network, Medical Image Analysis, Early Detection, Batch Normalization, Batch Size, Activation Function, Max Pooling.

ABSTRACT

Alzheimer's disease is a brain disorder that slowly damages memory, thinking, and behavior. Common symptoms include memory loss, confusion, mood changes, and trouble with daily tasks. There is no cure yet, but early diagnosis and treatment can help manage symptoms. In this work, deep learning is used to help detect Alzheimer's disease by analyzing brain MRI images. Convolutional Neural Network (CNN) is applied, which can learn to identify differences between healthy brains and those affected by Alzheimer's. MRI images of both healthy individuals and Alzheimer's patients were obtained from the OASIS dataset. The objective is to train the system to recognize patterns in these images and make a prediction about whether a person has the disease. Different CNN models like AlexNet, and ResNet50 are compared, along with a custom-built model. The performance of the proposed model is evaluated in terms of speed, computational complexity and accuracy.

INTRODUCTION

Alzheimer's disease, a neurogenerative disorder that primarily affects older individuals, it causes memory loss, cognitive decline, and behavioural changes. It is one of the most common causes of dementia, early detection helps to provide medical care and improving patient quality of life. Traditional diagnostic methods, including clinical examinations and neuropsychological tests remain time-consuming and often subjective. Hence the integration of advanced machine learning and deep learning techniques provides an approach for automated Alzheimer's detection. In this work, a Convolutional neural network (CNN) based model is used to classify brain MRI images as either healthy or Alzheimer's affected. For research and implementation OASIS data set is used which contains MRI images of both healthy persons and Alzheimer's patients. The images are first pre-processed by resizing them to 128×128 pixels, converting them in to grayscale, and normalizing intensity values to improve model consistency and accuracy.

The proposed CNN model utilizes multiple convolutional, pooling, and batch normalization layers are designed to extract relevant features from the MRI scans. Techniques like dropout, ReLU activation, and Adam optimization are used to improve training stability and avoid overfitting. The model was trained for up to 20 epochs, but smart checks were added: if the model stopped improving, it would automatically stop early, and if it was learning too slowly, the learning speed would adjust. This helped the model learn better and faster without wasting time. During the process, the custom model is compared with various CNN architectures like AlexNet, and ResNet50. This work helps improve the field of medical image analysis. It shows how a deep learning method helps doctors to detect Alzheimer's disease early. In the future, the model will be tested on bigger datasets. There are also plans to use it in hospitals as a tool to support doctors in making decisions.

LITERATURE REVIEW

Alzheimer's disease (AD) is a progressive neurodegenerative condition that impacts memory and cognitive skills, making early diagnosis essential for effective treatment. Early neuroimaging studies revealed both structural and perfusion-related abnormalities in AD. Johnson et al. [1] demonstrated that arterial spin-labelling MRI could detect early hypoperfusion patterns linked to AD and MCI. Traditional machine learning techniques such as SVM, Random Forests, and Decision Trees were widely used in early diagnostic systems; however, these required handcrafted features from MRI or PET scans. Cedazo-Minguez and Winblad [2] reported that such biomarker-based methods faced challenges due to dependence on human-designed features and limited generalization across diverse imaging datasets.

The introduction of deep learning significantly transformed AD detection. CNN-based models, motivated by major breakthroughs in large-scale image classification [4], enabled automatic extraction of discriminative features directly from brain images. These models outperformed traditional approaches in distinguishing healthy, MCI, and AD subjects. Further advances in multimodal fusion improved diagnostic accuracy by combining MRI and PET modalities, as demonstrated by Zhang and Shen [9]. Ensemble-based deep learning approaches also enhanced robustness in classification, providing more reliable predictions [12]. To handle limited or imbalanced datasets, researchers explored strategies such as transfer learning, data augmentation, and multimodal fusion. Liu et al. [15] confirmed that these techniques strengthened model stability and early AD detection, while studies like those of Basaia et al.[14] showed improved accuracy through the use of large clinical datasets.

Recent research emphasizes model transparency and generalization. Explainable AI techniques have become increasingly important for clinical adoption. Li et al. [22] applied Grad-CAM to highlight the brain regions influencing CNN predictions, enhancing interpretability and clinician trust. More recent studies, including Dardouri's [23] work on MRI data from the OASIS dataset, continue refining deep CNN architectures and show improved early detection performance. Overall, the field has shifted from traditional feature-engineered approaches to advanced deep learning systems, with current efforts focusing on multimodal integration, improved generalization across datasets, and explainable AI to ensure clinically reliable automated AD diagnosis.

METHODOLOGY

In this work, a Convolutional Neural Network (CNN)-based approach is used for the automatic detection of Alzheimer's disease using MRI images from the OASIS dataset. First, the dataset is pre-processed to ensure consistency and better learning. Each MRI image is resized to a fixed size, converted to grayscale to reduce computational complexity, and normalized so that pixel values lie between 0 and 1. These preprocessing steps help maintain data consistency, improve training stability, and enable the model to learn important features more effectively.

After preprocessing, a CNN model is implemented using TensorFlow and Keras with a sequential architecture consisting of four convolutional blocks. Each block uses a 5×5 kernel with 32 filters and appropriate padding to extract meaningful features from the MRI images. A batch size of 32 is used during training. Each convolutional block includes batch normalization, a ReLU activation function to introduce non-linearity, and a max-pooling layer to reduce the feature map size while preserving important structural information.

Figure 1 illustrates the end-to-end workflow for Alzheimer's disease detection using MRI images.

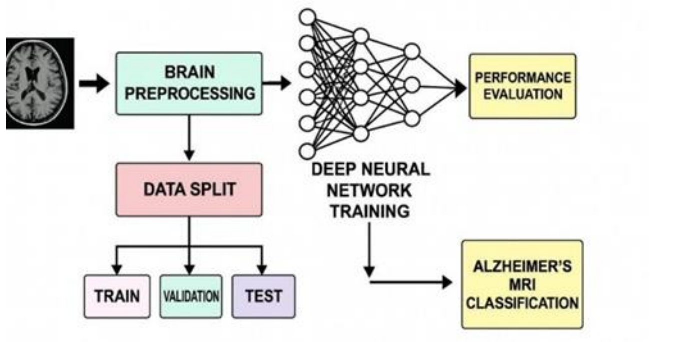


Fig. 1. End-to-End Workflow for Alzheimer's Detection Using MRI image

After feature extraction, the output is flattened and passed through a fully connected network consists of 512 neurons, with batch normalization, ReLU activation and a dropout layer to reduce overfitting and improve accuracy. The final output layer consists of a softmax activation function with four network neurons, and consists of four Alzheimer's disease categories.

The model is compiled using adam optimizer with a learning rate of 0.001 and a categorical cross entropy loss function, which is suitable for multi-class classification. During training, the model displays smooth convergence, achieving high training and validation accuracy. The learning curves of accuracy and loss are displayed using matplotlib to visualize the performance and stability of CNN.

Fig.2 Shows the architecture of CNN and this CNN-based approach provides a strong framework for automatically classifying the stages of alzheimer's disease using MRI data. By successfully combining feature extraction, normalization, dropout regularization, and adaptive optimization, the model provides high accuracy even in a CPU- based environment, and supports the real time clinical diagnostic applications.

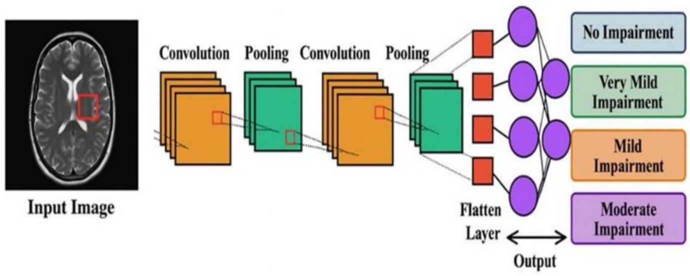


Fig.2. The architecture of Convolutional neural network

For comparative evaluation, transfer learning models such as AlexNet and ResNet50 were also implemented. These models use pre-trained weights to reduce training effort.

DATASET

This work uses the OASIS (Open Access Series Of Imaging Studies) MRI dataset, obtained from the Kaggle website. A publicly available and well-established benchmark widely used in Alzheimer's disease research. The dataset provides high resolution T1-weighted MRI scans from a wide range of subjects, including both healthy individuals and patients with dementia at different levels of cognitive impairment.

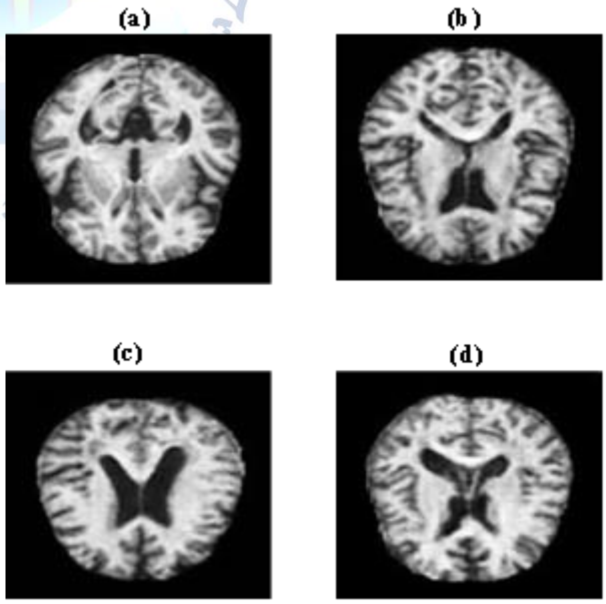


Fig. 3. (a) No Impairment (b) Very Mild Impairment (c) Mild Impairment (d) Moderate Impairment

In this work, 8000 MRI images from the dataset are used, classified into four different classes as shown in the fig.3: (a) No Impairment, (b) Very Mild Impairment, (c) Mild Impairment, and (d) Moderate Impairment. This classification makes the model to perform multi stage analysis and is not only used to detect the Alzheimer's disease but also able to differentiate the stages and it is a required factor for treatment planning.

The dataset is divided in to 80%, 10% and 10% - 80% for training, 10% for validation, and 10% for testing. This confirmed that the model is trained on sufficient amount of data.

EXPERIMENTAL SETUP

The experimental setup provides the hardware and software configurations to develop and evaluate the proposed CNN model for Alzheimer's disease classification. All experiments are conducted on a system with an intel core of i5 12th gen processor, 8 GB RAM, and a 512 GB SSD. Even without a fancy graphics card, the model was trained smoothly on a regular Windows 11 computer by tweaking the settings just right. Even though there was no high-end GPU, the model still gave really good results using just a CPU. This proves that the CNN model is both efficient and reliable for detecting Alzheimer's early.

TESTING AND MODEL EVALUTION

After completing the training process, the final CNN model was saved in the Keras (.keras) format. During the testing phase, this trained model is loaded using TensorFlow's load_model() function. For every test image, the system reads the image from disk using OpenCV in grayscale mode, resizes it to 128×128 pixels, normalizes the pixel values, and reshapes it to match the input shape used during training.

Once pre-processed, the image passes through the CNN's convolutional layers, where important spatial features are extracted. These learned features are then passed into fully connected layers that classify the image into one of four categories: a. No Impairment, b. Very Mild Impairment, c. Mild Impairment, d. Moderate Impairment.

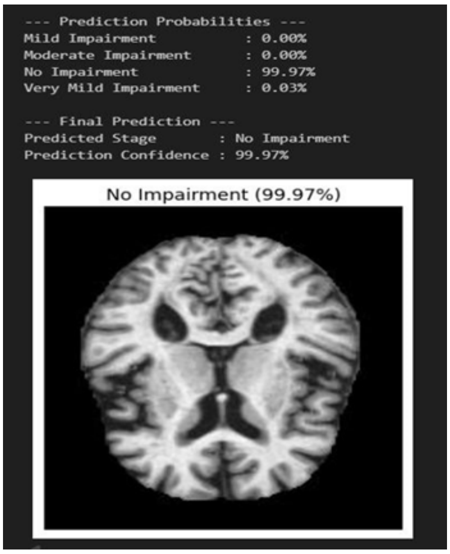


Fig. 4. Alzheimer's Stage Classification Output

The model outputs a probability score for each class, and the class with the highest probability is selected as the final prediction. Along with the predicted class, the confidence level is also displayed. Finally, the tested MRI image is shown using Matplotlib, with the predicted stage and confidence percentage annotated on the image.

This workflow enables real-time evaluation of MRI scans and clearly indicates the model's confidence in identifying the stage of cognitive impairment. Fig. 4 shows Alzheimer's stage classification output

RESULTS AND DISCUSSION

The CNN model is trained using a collection of brain MRI scans to identify different stages of cognitive health. The model was trained successfully and demonstrated robust performance, indicating its effectiveness on unseen data. Fig.5: Shows Training and Validation accuracy of the proposed CNN model. The model achieved a training accuracy of 99.96% and a validation accuracy of 98.25%, indicating strong convergence and generalization. The Adam optimizer helped the model learn efficiently.

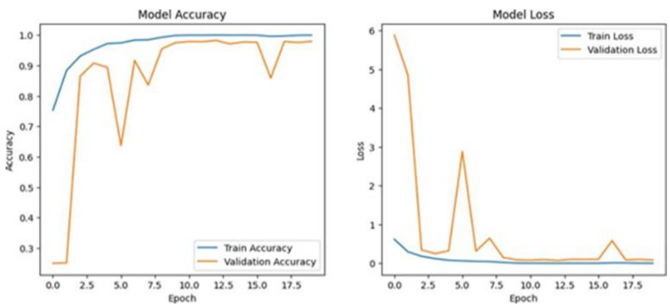
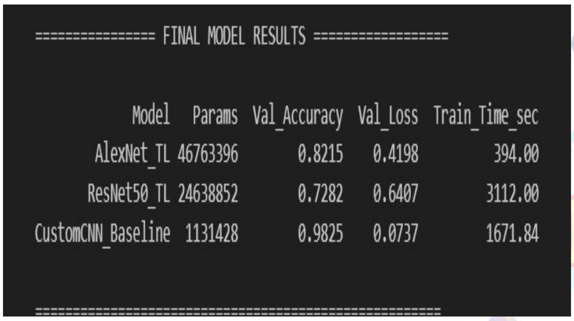


Fig. 5. Training and validation accuracy of the proposed CNN model

The model achieved over 95% confidence on unseen test images, accurately identifying Alzheimer's stages. This model is compared with architectures like AlexNet and ResNet50, the proposed model achieved good accuracy with lower computational cost. Fig. 6. illustrates the comparison between custom CNN model and various CNN architectures.



============== FINAL MODEL RESULTS ================

Model	Params	Val_Accuracy	Val_Loss	Train_Time_sec
AlexNet_TL	46763396	0.8215	0.4198	394.00
ResNet50_TL	24638852	0.7282	0.6407	3112.00
CustomCNN_Baseline	1131428	0.9825	0.0737	1671.84

Fig. 6. Fnal Model Evaluation Results for All Compared Architectures

According to Fig. 7, Performance Trend Comparison of AlexNet, ResNet50, and Custom CNN the results clearly show that the Custom CNN Baseline model works the best among all the tested models. It gives the highest accuracy (98.25%) and the lowest loss, which means it makes more correct and reliable predictions.

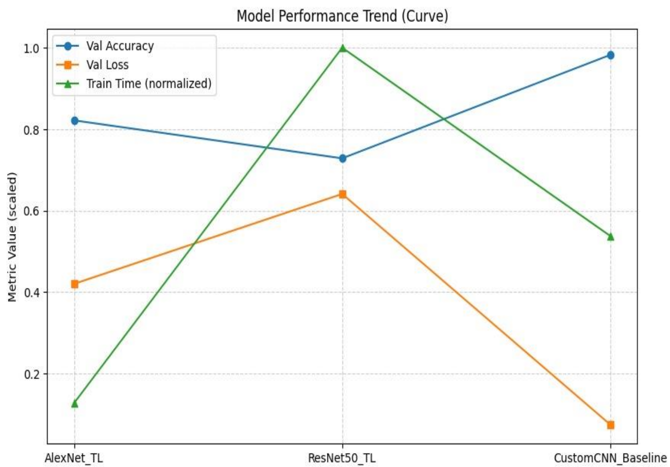


Fig. 7. Performance Trend Comparison of AlexNet, ResNet50, and Custom CNN

As further illustrated in Fig. 8, Combined Validation Accuracy, Loss, Training Time, and Model Size Comparison, the custom CNN also demonstrates better efficiency with fewer parameters and reasonable training time. Even though this model is simpler and has fewer parameters, it still performs better than both AlexNet and ResNet50. AlexNet trains faster but does not achieve high accuracy, while ResNet50 takes much longer to train and still gives lower accuracy. Overall, the Custom CNN model offers the best combination of accuracy and efficiency, making it the most suitable model for this work.

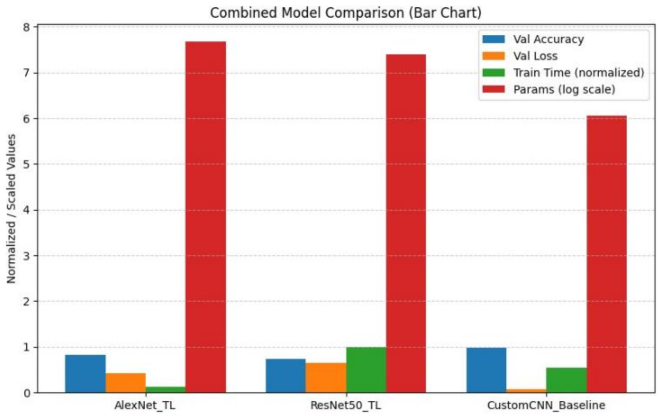


Fig. 8. Combined Validation Accuracy, Loss, Training time, and Model Size Comparison

CONCLUSION

In this work, a Convolutional Neural Network (CNN)-based deep learning model was Successfully developed to detect and classify the stages of Alzheimer's disease using brain MRI images from the OASIS dataset. The proposed CNN architecture effectively extracted complex features from MRI scans and achieved high validation accuracy. The proposed CNN performed better than AlexNet and ResNet50, achieving higher accuracy with improved efficiency. During testing, the model provided accurate predictions with high confidence levels, highlighting its reliability in real-world applications. Future research focuses on expanding dataset size, and enable the model work with 3D MRI data, and deploying the model as a web based clinical decision support tool for real time diagnosis.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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