A Deep Learning Approach for Alzheimer's Disease Detection Using Convolutional Neural Networks

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Abstract—**In this study, we developed and evaluated convolutional neural network (CNN) architectures for the classification of Alzheimer's Disease using medical imaging data. The research focused on optimizing model configurations, including the number of convolutional blocks, filter sizes, kernel sizes, dense units, dropout rates, and activation functions, to improve classification accuracy and computational efficiency. Leveraging the NVIDIA A100-SXM4-40GB GPU, we conducted rapid training and experimentation, facilitating the fine-tuning of model parameters.**

Key configurations involved the use of ReLU and Leaky ReLU activation functions, selected for their ability to introduce non-linearity, mitigate the vanishing gradient problem, and enhance feature extraction. Additional convolutional blocks were incorporated to capture complex patterns, particularly important for detecting subtle changes in brain scans indicative of Alzheimer's Disease. A dataset split of 80% for training (4097 images) and 20% for validation (1024 images) was employed, with a reduced training period of 200 epochs to prevent overfitting and expedite the learning process.

Among the models tested, the highest accuracy of 96.4% was achieved by a CNN configuration comprising four convolutional blocks with progressively increasing filters (32, 64, 128, 256), ReLU activation, and max pooling. This model's success is attributed to its balanced architecture and effective dropout strategy, which promoted generalization while minimizing overfitting. Conversely, more complex models with additional convolutional blocks or alternative activation functions such as ELU or Tanh exhibited lower accuracy, underscoring the challenges of overfitting and optimization in deeper networks.

The results demonstrate the critical role of careful model design and the use of advanced computational resources in achieving high accuracy in Alzheimer's Disease classification. This study highlights that while deeper networks can enhance feature extraction, optimal performance is contingent on appropriate activation functions, dropout rates, and model complexity.

Index Terms— **Alzheimer’s disease classification, GPU acceleration, NVIDIA A100 GPU, CNN, ReLU Activation, Medical Imaging**

I. INTRODUCTION

The most well-known cause of dementia in people 65 years of age or older is Alzheimer's disease (AD). It is a progressive, permanent neurological illness that progresses according to a certain pattern of mental damage. One very common type of dementia is Alzheimer's infection [1]. The term dementia is used to describe a broad range of illnesses and disorders that arise when neurons, or nerve cells in the brain, die or stop functioning on a regular basis [2]. Memory loss is the most typical sign of this illness. The first symptom is difficulty recalling previous talks and conversations. As time passes on, there are numerous more symptoms that become more prominent. Brain abnormalities associated with this illness cause more problems with memory, reasoning, and thinking skills, as well as personality and behavior changes, mood swings, sadness, and other issues. Everybody occasionally experiences memory loss, but Alzheimer's disease-related memory loss impairs a person's capacity to operate both at work and at home. A person suffering from this illness may repeat statements again and forget what was said in the conversation.

One in 85 persons may have AD by the year 2050, according to the results of the earlier study [3]. In the early stages of AD patients' condition, diagnosis and preventive measures are crucial. While there are several methods available for the detection and prediction of this dementia using MRI, PET, and CT scans, the most common and impacted neuroimaging technique is the diagnosis of AD patients using MRI examinations. According to an Alzheimer's Association research, the US is expected to spend $1.1 trillion on AD and other dementias by the year 2050. Physically analyzing AD or some other types of dementia in its early stages before most of its symptoms become noticeable is challenging.

Deep learning is an artificial intelligence subfield of machine learning that, thanks to its numerous layered and/or ordered structure network, enables the machine to learn classification tasks from raw data [4][5]. CNN is the most used deep learning algorithm due to its high success rate in analysis and image classification [6][7][8]. CNN is used in neural networks to extract high-level features from picture classification and prediction. It consists of three stages: feature extraction, classification, and picture pre-processing. Edge detection and cropping of MRI brain pictures complete the image processing during the pre-processing step. The classification of brain pictures is then accomplished using CNN model classifier layers using feature extraction [9]. Because Alzheimer's patients' brain patterns and pixel intensities are similar, diagnosing Alzheimer's in older adults is quite challenging and calls for a highly discriminative feature representation. The major goal is to create the finest prediction and detection tools to assist physicians, radiologists, and other caregivers in saving time and money while also assisting the patient who is afflicted with this illness.

II. Background and Prior Work

A. Dataset

We have collected our dataset from Kaggle. The dataset consists of MRI images of humans who suffer from dementia in different stages and MRI images of healthy people. The dataset consists of 4 classes (Non-Dementia, Very Mild Dementia, Mild Dementia, and Moderate Dementia) as shown in Fig. 1. The dataset consists of a total of 6400 images, out of which, the test data consists of 1279, and train data consists of 5121 images. The dataset is highly unevenly distributed among all the 4 classes. For example, Non-Dementia and Very Mild Dementia have over 2000 and 1400 images each respectively. While the other two groups Mild Dementia, and Moderate Dementia have 573 and 42 images respectively. This ratio is also similar in test data. This non-uniform distribution of the dataset creates challenges while training the CNN models. To make them evenly distributed, up-sampling can be done. However, this can cause overfitting of the model as we train the model with the same images again and again with none to very little change.

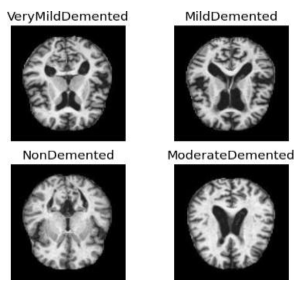


Fig. 1 MRI images of different classes in the dataset

B. Hardware

We used NVIDIA A100-SXM4-40GB GPU in Colab for all computational needs. It will take a very long time if we run it on the CPU. We also recommend using GPU over CPU for all computational needs.

C. Literature Survey

Many researchers have worked on the detection algorithms of AD and proposed many techniques. [10][11] proposed 2 methods using zero masking and SAE for feature learning & Classification, and another method using a multiphase feature approach combined with SAE for classification. Both the methods were able to achieve only around 50% – 60%. A SAE is also a neural network architecture that is composed of multiple layers of autoencoders. Encoder mas the input data to a lower-dimensional latent space representation and decoder uses this data to reconstructs the input data. The output of one autoencoder is given to input of another autoencoder. [12] employed SDPNs for classification. Separate SPDNs were used for MRI and PET data and their outputs were fused to final SDPN layer and achieved a 57% accuracy which is higher than the traditional image processing techniques. SDPNs use polynomial activation functions instead of traditional non-linear activation. This complex relation helps neural networks to learn more complex patterns than traditional neural networks.

A very significant change is observed in the accuracy when SAE and convolution techniques are used to learn features for classification [13]. This method achieves an accuracy of 85%. Similarly, another methos performed 3D convolution with MRI data and obtained an accuracy of 89.5% [14]. Another method approach proposes a feature extraction method. A total of six features were extracted. After the data processing, model training is carried out for classifier algorithms like SVM, Logistic Regression, and Random Forest and tested with test data [15]. This method achieved the highest accuracy of around 60% for multi-class classification and slightly higher for binary classification.

Another approach is to combine two classification techniques for better accuracy. [16] proposes a hybrid-ML technique by combining SVM and KNN from ADNI dataset and achieved an accuracy of 99%. [17] also uses CNN approach for ADNI dataset with 3 classes of images that achieved an accuracy of 99%. [18] uses state-of-the-art complex CNN architectures GoogLeNet and ResNet and achieved an accuracy of 98.88% and 98.01% respectively. The above discussed methods are aggregated into Table1.

TABLE I
Accuracy and Technology Proposed by Some Methods

Approach	Technique	Accuracy (%)
Lui et al.	SAE + Zeromask	53.8
Jun Shi et al	SDPN	57
Lui et al.	MPFR	59.19
Gupta et al	SAE + Convolution	85
Payan et al.	SAE+ 3D CNN	89.4
Pranao et al.	Feature Extraction	60.4%
Salehi et al.	CNN	99%
Senthil Kumar et al	Hybrid-ML (SVM + KNN)	99%
Farooq et al	GooLeNet, ResNet	98.88%, 98.01%

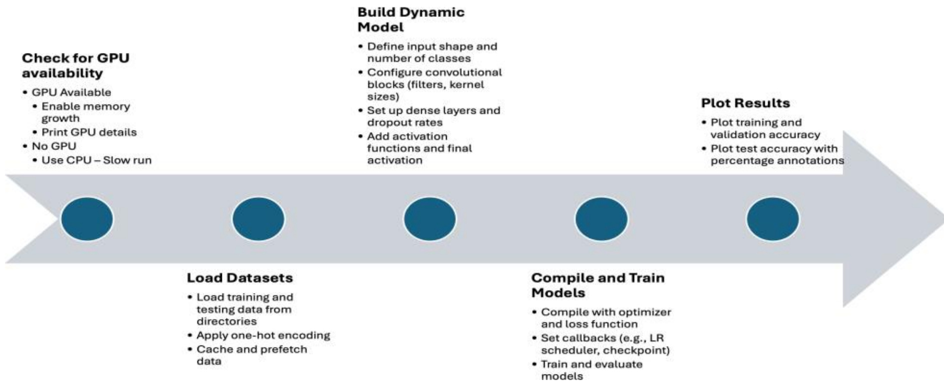


Fig. 2 Methodology of the Proposed Technique.

III. METHODOLOGY

A. Check for GPU availability

Initially, we will check for GPU availability in the environment. If it is present, we print the GPU details, and our method utilizes this GPU for faster computational power to make the process faster. If there is no GPU available, the model building, training, and results are computed on the CPU. We used NVIDIA A100-SXM4-40GB GPU to perform all computations.

B. Load Datasets

Next, we load both training and test datasets from the directory. A split of approximately 80% for training and 20% for validation is a common practice to ensure that the model has enough data to learn from while also being able to validate its performance on unseen data. This helps in fine-tuning the model and improving its generalization capability. We used 4097 images for training and 1024 for testing.

C. Model Building

As shown in Fig. 2, we are going to build our model by configuring the convolutional blocks. We select a different number of layers, different filter sizes (32, 64, 128, etc..), kernel sizes (3, 5, 7, 9, etc..). Then we set up our dense layers and dropout rates for the model. Finally add the activation functions such as ReLu, ELU, Sigmoid, etc.. and the final activation layer. As we have implemented six CNN models, we kept changing these parameters to obtain maximum classification accuracy. A detailed discussion of how we have selected these parameters is discussed in Section 4.

D. Compilation and Training

After building the model, we then compile the model. If we encounter any errors, we rectify these errors and train the model for the desired number of epochs. Epoch values are kept as minimum as possible to train the modules faster, allowing quicker iterations and experimentation. Given the powerful GPU (NVIDIA A100-SXM4-40GB) and the number of files, 200 epochs can strike a balance between training time and preventing overfitting, especially since you have a validation set in place to monitor the model's performance.

E. Compilation and Training

Once the model is trained, we plot the training and validation accuracy for every epoch value and then compute the test accuracy of the model using the test dataset.

IV. EXPERIMENTAL RESULTS

We have trained 6 different models with varying architectures with different configurations of convolutional blocks, filters, kernel sizes, dense units, dropout rates, activation functions, and the use of max pooling which are shown in Fig. 3.

When selecting model configurations, we considered several factors to optimize the accuracy and efficiency of your Alzheimer's Disease classification framework:

Activation Functions: We choose activation functions like ReLU or Leaky ReLU. ReLU is widely used because it introduces non-linearity and helps the model to learn complex patterns. It’s computationally efficient, avoids the vanishing gradient problem, and works well in deep networks, improving training speed and accuracy.

Additional Convolutional Blocks: We have added more convolutional layers. Additional convolutional blocks can help the model capture more complex features and patterns from the image data. For Alzheimer's classification, where subtle differences in brain scans need to be detected, deeper networks can learn these intricate patterns better, thus improving accuracy.

Impact on Accuracy: Overall, by varying the configurations of convolutional blocks, filters, kernel sizes, dense units, dropout rates, activation functions, and the use of max pooling, the accuracy has been impacted due to the following reasons.

Improved Feature Extraction: With additional convolutional layers and ReLU activation, the model can learn more complex features, leading to better classification accuracy.

Balanced Training: The reduced epochs, combined with the dataset split, help in preventing overfitting while ensuring that the model generalizes well to unseen data.

MODEL	CONV BLOCKS	FILTERS	KERNEL SIZE	DENSE UNITS	DROPOUT RATES	ACTIVATION	MAX POOLING	FINAL ACTIVATION	TEST ACCURACY	TEST AUC
1	4	32, 64, 128, 256	3, 3, 3, 3	512, 128, 64	0.7, 0.5, 0.3	ReLU	Yes	Softmax	96.39	99.30
2	5	32, 64, 128, 256, 512	3, 3, 3, 3, 3	1024, 512, 256	0.5, 0.5, 0.4	ReLU	Yes	Softmax	49.71	68.31
3	3	64, 128, 256	3, 3, 3	256, 128	0.4, 0.3	ELU	No	Softmax	1.2	36.19
4	3	64, 128, 256	3, 5, 7	512, 256	0.5, 0.3	Leaky ReLU	Yes	Softmax	51.66	74.48
5	4	32, 64, 128, 256	3, 3, 5, 5	1024, 512, 256, 128	0.6, 0.4, 0.3, 0.2	Sigmoid	No	Softmax	49.51	77.67
6	5	32, 64, 128, 256, 512	3, 3, 3, 5, 7	2048, 1024	0.7, 0.5	Tanh	Yes	Softmax	34.86	64.71

Fig. 3 Model Configurations for the six CNN models considered

Efficiency and Experimentation: Leveraging the A100 GPU allows for rapid training, which is crucial for experimenting with different configurations to find the most accurate model.

Overall, these configurations aim to balance the depth and complexity of the model with efficient training, leading to higher accuracy in classifying Alzheimer's disease. Fig. 4 shows the train accuracy and validation accuracy plots for CNN models 1-6. The test accuracy chart (Fig. 5) reflects how well each model performs on the test dataset.

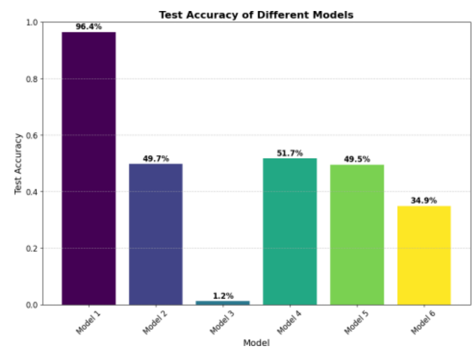


Fig.5 Test Accuracy of 6 CNN Models

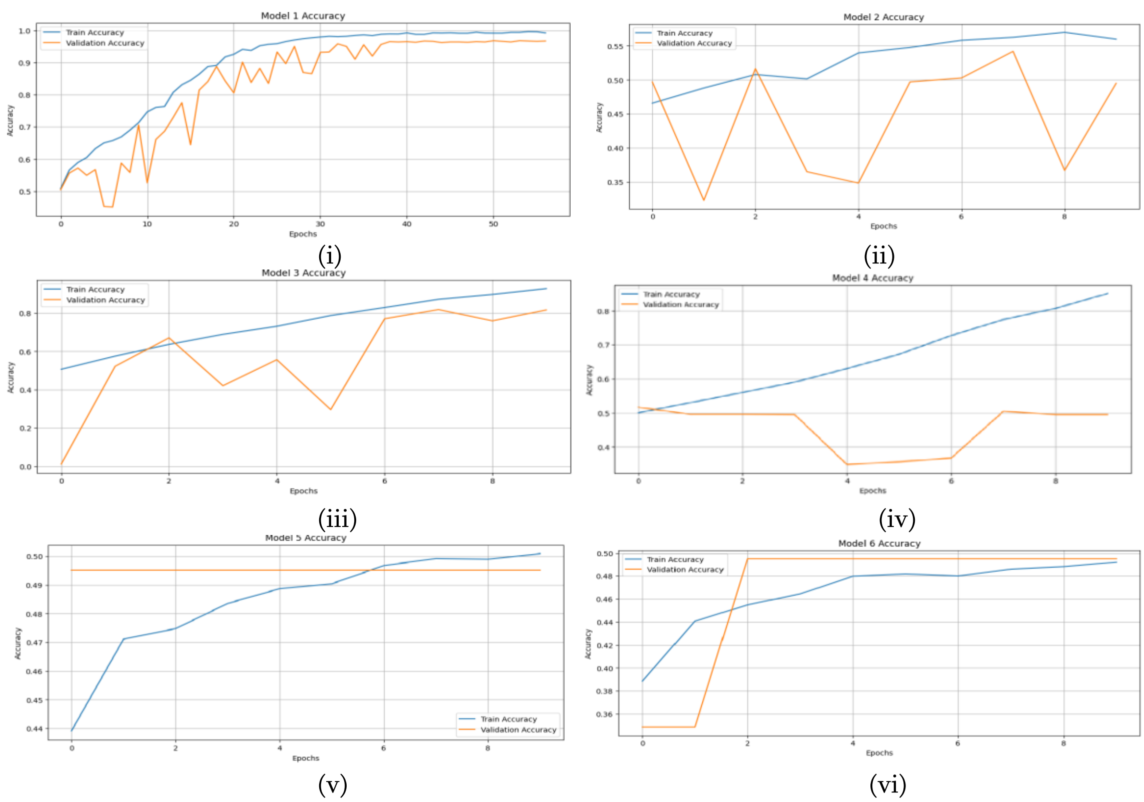


Fig. 4 Training accuracy and Validation accuracy for CNN models 1 – 6. (i) Model 1, (ii) Model 2, (iii) Model 3 (iv) Model 4, (v) Model 5, (vi) Model 6

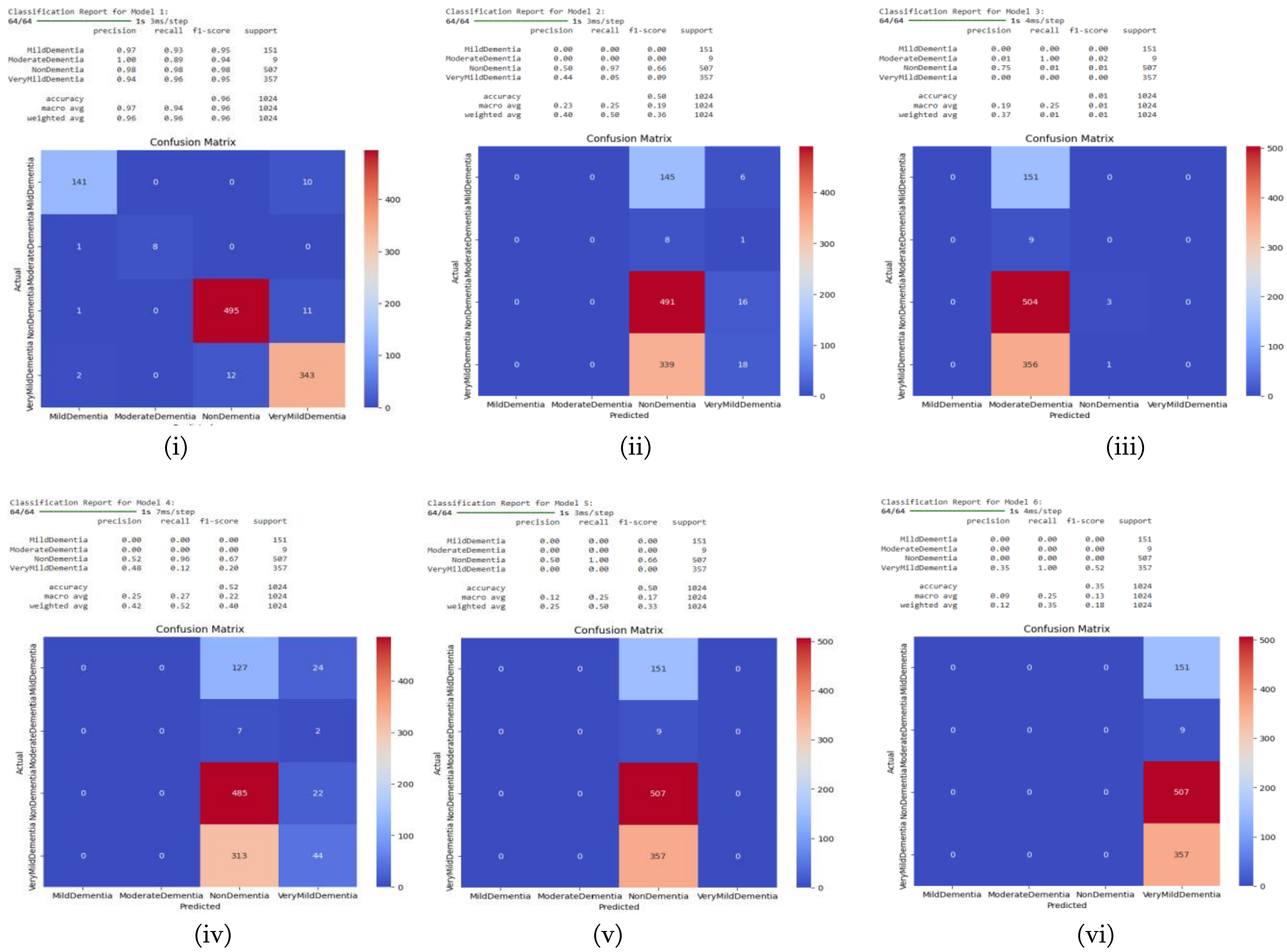
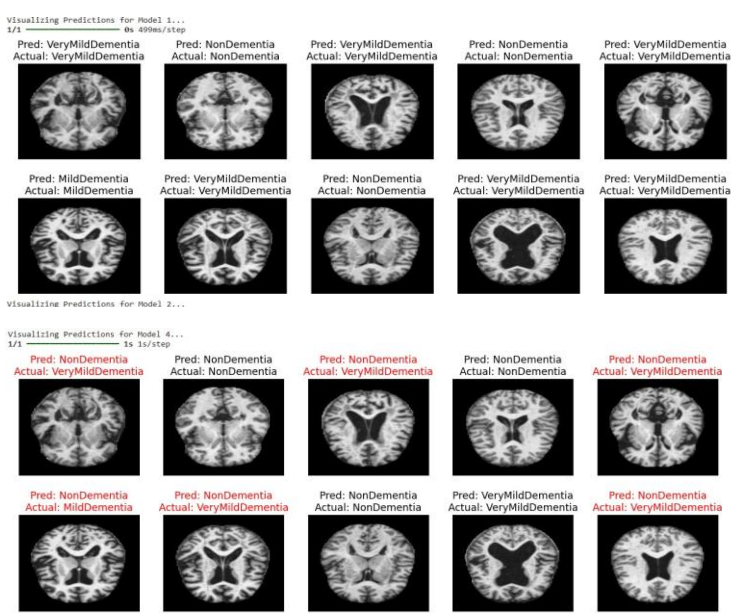


Fig. 6 Confusion Matrix for CNN models 1 – 6. (i) Model 1, (ii) Model 2, (iii) Model 3 (iv) Model 4, (v) Model 5, (vi) Model 6



(ii)

Fig. 7 Actual vs Predicted MRI images for (i) Model-1, (ii) Model-4

V. Conclusion

In this study, we have proposed a convolutional neural network classification algorithm for AD using MRI images. Four classes of images with a total number of 6400 images were used in this study. Model 1 stands out as the best-performing model, likely due to its balanced architecture with effective use of ReLU, max pooling, and appropriate dropout rates. A significant accuracy of 96.4% has been achieved. Model 3 is the worst-performing model, indicating that its simpler architecture and lack of max pooling led to poor feature extraction and generalization. The other models exhibit varying degrees of underperformance, likely due to either over-complexity, suboptimal activation functions, or issues with overfitting. Overall, these configurations aim to balance the depth and complexity of the model with efficient training, leading to higher accuracy in classifying Alzheimer's disease.

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