Early detection of Alzheimer's disease using Neuro imaging and Deep learning techniques

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***Abstract*—Accurately diagnosing the stages of Alzheimer's disease (AD) using MRI images poses a challenge for human doctors, as even experienced professionals can make mistakes. Traditional solutions heavily rely on various MRI pre-processing techniques to improve diagnostic accuracy. In recent years, deep learning methods, particularly Convolutional Neural Networks (CNNs), have shown promise in Alzheimer's disease diagnosis through classification approaches. However, there is still a need to bridge the research gap in utilizing deep learning techniques for object detection in Alzheimer's disease diagnosis. In this research, we conduct comprehensive comparisons and explore various techniques to address this gap, aiming to identify the most effective approach for solving this diagnostic challenge.**

Firstly, we introduce hyperparameter tuning in our CNN model to identify the best parameters for achieving optimal accuracy, considering execution time. Next, we compare the accuracy and loss metrics of various CNN architectures, including EfficientNet, ResNet50, VGG16, InceptionV1, and AlexNet, while also assessing their respective execution times. Additionally, we examine the impact of dataset augmentation techniques and the number of data samples on accuracy, loss, and execution time. Furthermore, we evaluate the effects of different hyperparameter tuning methods and batch sizes, along with their associated execution times. Our proposed CNN model incorporates the latest techniques, featuring the EfficientNetV2S architecture version2. As a result of our research, we provide a benchmark for the deep learning-based Alzheimer's disease stage detection, categorizing individuals into four stages: Mild Demented, Moderate Demented, Non Demented, and Very Mild Demented. The utilization of the dataset we using MRI data from the ADNI through Kaggle, with its extensive 2D sliced MRI data for each stage, enables the extraction of meaningful features and patterns associated with Alzheimer's disease pathology. The outcomes of this study contribute to the advancement of diagnostic tools and therapeutic interventions, enhancing the understanding and management of Alzheimer's disease.

Keywords*— *Alzheimer's disease (AD), Convolutional Neural Networks (CNN), Deep learning, MRI

I. INTRODUCTION

Alzheimer's disease stands as a progressive neurodegenerative condition mainly impacting the elderly demographic. This ailment represents the predominant type of dementia, encompassing around 60-80% of instances of dementia. Its defining features encompass the buildup of anomalous protein formations like beta-amyloid plaques and tau tangles within the brain. Consequently, this process results in the gradual deterioration of cognitive capabilities.

Based on the most recent information released by the World Health Organization (WHO) in 2020, the recorded fatalities attributed to Alzheimer's and dementia in Sri Lanka amounted to 6,939, constituting approximately 5.98% of the overall reported deaths. This data also indicates an age-adjusted mortality rate of 27.62 per 100,000 individuals, positioning Sri Lanka at the 14th position on a global scale. For further insights into alternative causes of mortality, you may consider utilizing the provided hyperlinks or accessing the comprehensive health profile [1].

As people advance in age, the likelihood of developing Alzheimer's disease escalates. Despite ongoing research, the precise origins of this condition remain incompletely elucidated, age is considered the greatest known risk factor. Other risk factors include genetics, family history, lifestyle factors (such as diet and exercise), cardiovascular health, and certain medical conditions.

By leveraging deep learning techniques, researchers aim to develop more accurate and reliable methods for early detection, This holds the potential to discern individuals with an elevated susceptibility to Alzheimer's disease prior to the manifestation of pronounced symptoms. This can lead to better management of the disease, improved quality of life, and the development of targeted therapies for those at risk of progression to more severe stages of the disease leads to death.

Two significant magnetic resonance imaging (MRI) repositories, namely the Alzheimer Disease Neuroimaging Initiative (ADNI) [2] database and the Open Access Series of Imaging Studies (OASIS) [3] database, have been established to aid doctors and researchers in the field of Alzheimer's disease. The ADNI database is a renowned research project that offers a comprehensive dataset comprising MRI scans from individuals at different stages of the disease, including normal cognition, mild cognitive impairment (MCI), and Alzheimer's dementia. This database not only includes MRI data but also encompasses clinical and genetic information, biomarker measurements, and cognitive assessments. ADNI has made significant contributions to the understanding of Alzheimer's disease and has been extensively utilized in research studies and clinical trials. On the other hand, the OASIS database provides a publicly accessible dataset featuring MRI scans from individuals with varying cognitive abilities, including healthy individuals, Alzheimer's disease patients, and those with MCI. The dataset is enriched with diverse demographic information and clinical assessments, enabling researchers to investigate different aspects of Alzheimer's disease progression. Both the ADNI and OASIS databases have played instrumental roles in advancing Alzheimer's disease research by facilitating the development and evaluation of diagnostic algorithms, exploration of biomarkers, and examination of disease progression. These valuable resources have contributed to a deeper uderstanding of the structural and functional brain changesn associated with this disease and have paved the way for the development of more accurate diagnostic tools and potential treatment strategies.

In situations we facing permission issues and delays for the process in obtaining data from databases like ADNI and OASIS, so we turn to alternative sources such as Kaggle to access Alzheimer's disease-related MRI data. Kaggle is a popular online platform that hosts a wide range of datasets and provides a collaborative environment for data science and machine learning projects, provides datasets related to various topics, including Alzheimer's disease.

In our research project, we have chosen the Google Colab [4] platform as our computational tool. The primary reason for selecting Google Colab is its offering of free GPU resources and ample storage space on Google Drive, which are advantageous for our project requirements. The availability of free GPU resources significantly enhances the performance of our deep learning tasks, while the storage space on Google Drive allows us to conveniently store and manage our datasets.

The utilization of GPUs (Graphics Processing Units) in deep learning tasks, such as training Convolutional Neural Networks (CNNs), is highly beneficial. GPUs are specifically designed to handle parallel processing, which can dramatically accelerate the computational processes involved in training complex neural network models. By utilizing the free GPU resources provided by Google Colab, we can leverage the power of parallel computing to expedite the training and inference processes. This enables us to iterate and experiment more efficiently, ultimately improving the overall performance of our deep learning models.

Additionally, we have invested in Colab Pro, a subscription-based upgrade offered by Google Colab. Colab Pro provides several benefits compared to the free version. With Colab Pro, we have access to faster GPUs and increased memory, allowing us to handle larger and more computationally demanding comparisons and experiments. The improved performance and increased resources provided by Colab Pro further enhance our research capabilities, enabling us to conduct more extensive comparisons, explore complex CNN architectures, and optimize our models more effectively.

CNNs are a key technique in Deep Learning and have made significant contributions to the field of computer vision. Here is a brief overview of some notable CNN architectures we used. LeNet is an early CNN architecture developed by Yann LeCun. It consists of convolutional layers, pooling layers, and fully connected layers. LeNet was designed for digit recognition tasks and played a foundational role in the development of CNNs, GoogLeNet (Inception v1) also known as Inception v1, was developed by Google researchers. It introduced the concept of the Inception module, which performs parallel convolutions at different scales, allowing the network to capture features at multiple levels of complexity. ResNet is a groundbreaking CNN architecture that introduced the concept of residual connections. These interconnections facilitate the training of highly intricate networks by mitigating the challenge of the vanishing gradient issue. ResNet designs, including ResNet-50 and ResNet-101, have demonstrated impressive efficacy in tasks related to image recognition. On the other hand, the VGG network stands out for its straightforwardness and consistent structure. It comprises multiple convolutional layers featuring compact receptive fields, succeeded by max-pooling layers. VGG architectures, such as VGG16 and VGG19, are widely used and have demonstrated strong performance in image classification tasks. The Inception architecture comprises multiple versions, with each version employing inception modules. These modules utilize filters of different sizes to capture features at various scales, enabling the network to have a broader receptive field. AlexNet stands as a pioneering convolutional neural network (CNN) architecture that achieved victory in the 2012 ImageNet Large-Scale Visual Recognition Challenge. It played a pivotal role in popularizing the utilization of deep neural networks for the purpose of image classification tasks, showcasing their exceptional capabilities. AlexNet is structured with convolutional layers, pooling layers, and fully connected layers. EfficientNet is a recent CNN architecture that has gained attention for achieving state-of-the-art performance while maintaining computational efficiency. It employs a compound scaling method to balance model depth, width, and resolution, resulting in optimal performance we use in our project.

We are the group firstly using Hyperparameter tuning [5] in our CNN model, Hyperparameter tuning is a critical aspect of machine learning model development, aimed at finding the optimal values for the hyperparameters that govern the performance of the model. Hyperparameters, such as (lr) learning rate, batch size, Number of Hidden Layers, Dropout Rate and Kernel size set before the learning process and influence how the CNN model learns and generalizes from the data.

The advantages of hyperparameter tuning we face are manifold. By fine-tuning the hyperparameters, the performance of a machine learning (ML) model able to significantly improved. Optimal hyperparameters enable the model to converge fastest during training, reducing overall training time. They also enhancing model's ability to generalize well to unseen datas, making it more robust and avoiding issues such as overfitting or underfitting. We are utilizing the Random Search hyperparameter tuning technique in our CNN model. It proves to be an efficient approach as it reduces execution time by randomly sampling from the search space. This technique explores a wide range of hyperparameter combinations, allowing for the quick identification of promising configurations. Consequently, Random Search becomes a practical choice when time constraints are a concern, facilitating the attainment of optimal solutions in a more time-effective manner. Furthermore, several other techniques are available for tuning. These include Bayesian Optimization, Grid Search, Genetic Algorithms, and Sequential Model-Based Optimization (SMBO).

We are utilizing the Keras Tuner library to import the Random Search hyperparameter tuning technique. Additionally, there are several platforms and libraries that provide convenient methods for performing hyperparameter tuning. The scikit-learn library offers tools for both Grid Search and Randomized Search. Deep learning frameworks such as Keras and TensorFlow include built-in functionality for hyperparameter tuning, such as the Keras Tuner and TensorFlow's Hyperparameter Tuning capabilities. Furthermore, open-source libraries like Optuna and Ray Tune provide scalable and flexible options for hyperparameter optimization. These platforms and libraries offer efficient and effective ways to fine-tune hyperparameters and enhance the performance of our model. By leveraging these hyperparameter tuning techniques and platforms, researchers and practitioners can optimize their machine learning models, achieve better performance, and save time by automating the search for the most effective hyperparameter configurations.

This paper is organized in the subsequent manner. Section II we provide a literature review of contemporary developments in employing Deep Learning techniques for diagnosing Alzheimer's Disease, alongside an examination of prevailing Deep Learning approaches for Object Detection. Section III covers the methodology of encompasses the details of data preprocessing and the strategies employed in training. Our experimental findings are outlined and deliberated (Results and Discussions) upon in Section IV. Ultimately, in Section V, we encapsulate our study's conclusions and delineate potential directions for future research.

II. RELATED WORK

A. *Deep Learning for Alzheimer's Disease detection*

Various state of the art methods have been employed for the diagnosis of AD in the reviewed papers. These methods primarily leverage advanced technologies such as deep learning, machine learning, neuroimaging, and natural language processing. Some research papers have utilized deep learning algorithms, such as CNNs, to develop accurate classification models for Alzheimer's disease (e.g., [6], [11], [14], [15], [20], [22], [29], [30], [31]). Others have focused on leveraging multiple data modalities, including MRI, PET, and clinical information, to improve the accuracy of disease diagnosis and prediction (e.g., [13], [17], [19], [24], [27], [28], [38]). Furthermore, researchers have explored the use of gait analysis, speech data, and genetic factors in combination with deep learning and machine learning approaches to detect early stages of Alzheimer's disease (e.g., [7], [16], [25]). Additionally, advancements in model architectures, such as the modified EfficientNet [35], and the development of models like DEMNET and EfficientNet (e.g., [33], [36]), have contributed to accurate and timely diagnosis. Additionally, deep learning detection networks bypass MRI pre-processing steps [8], while others focus on brain segmentation and classification using 3D T1-weighted volumetric images [9]. Spatiotemporal feature extraction and classification [10], multimodal deep learning models [13][18][38],

Other approaches include the evaluation of neuroimages [29], the use of ensemble-based algorithms [28], and the prediction of AD progression [25][27][33]. these papers collectively demonstrate the effectiveness of deep learning and machine learning approaches in detecting, diagnosing, and predicting AD, and effective management of the disease. showcasing the potential for improved healthcare outcomes in the future.

B. *Accuracy according to techniquies*

Several research have been conducted to detect AD using different techniques and achieving varying levels of accuracy. In the [20], a CNN was used to detect AD from MRI images, achieving an accuracy of 92.5%. Similarly, [27] employed a deep learning model on MRI images and medical data to predict the progression of mild cognitive impairment to AD, achieving an accuracy of 93.1%. An ensemble-based machine learning algorithm was utilized in [28] to predict the conversion from mild cognitive impairment to AD, achieving accuracy of 89.6%. In [25], Natural Language Processing (NLP) was employed to analyze speech data and identify features indicative of AD, resulting in an accuracy of 88.2%. Furthermore, [26] used machine learning techniques on various features, including patient demographics, clinical data, and imaging data, achieving an accuracy of 87.5%. Another study used a CNN on resting-state fMRIs and reached an accuracy of 94.19% in detecting AD [6]. Similarly, [12] used a CNN on MRIs and obtained an accuracy of 87.7%. [14] utilized a CNN on MRIs and achieved an accuracy of 85.7%. The use of a 3D-CNN in [15] yielded an accuracy of 83.3% in detecting AD from MRIs. Machine learning techniques were also applied in [16] to detect AD, resulting in an accuracy of 82.4%. A cascaded CNN was employed in [17] on MRI images, achieving an accuracy of 80.8%, [13] used a CNN on MRIs, obtaining an accuracy of 80.2%. [19] employed a multi-modal CNN on MRI and PET images, achieving an accuracy of 79.5% in detecting AD.

Finally According to [39], the current trend in Alzheimer's Disease diagnosis involves the use of classification methods coupled with various MRI pre-processing techniques. Notably, Sarraf [40] and [41] achieved a test accuracy of 98.80% and 99.90%, respectively, in the Alzheimer's disease (AD) or is cognitively normal (NC) binary classification category. In this paper, our primary objective is to attain a comparable more test accuracy to Sarraf's findings with and without the need for any MRI pre-processing techniques.

III. METHODOLOGY

Here is your flowchart for early detection of Alzheimer's disease.

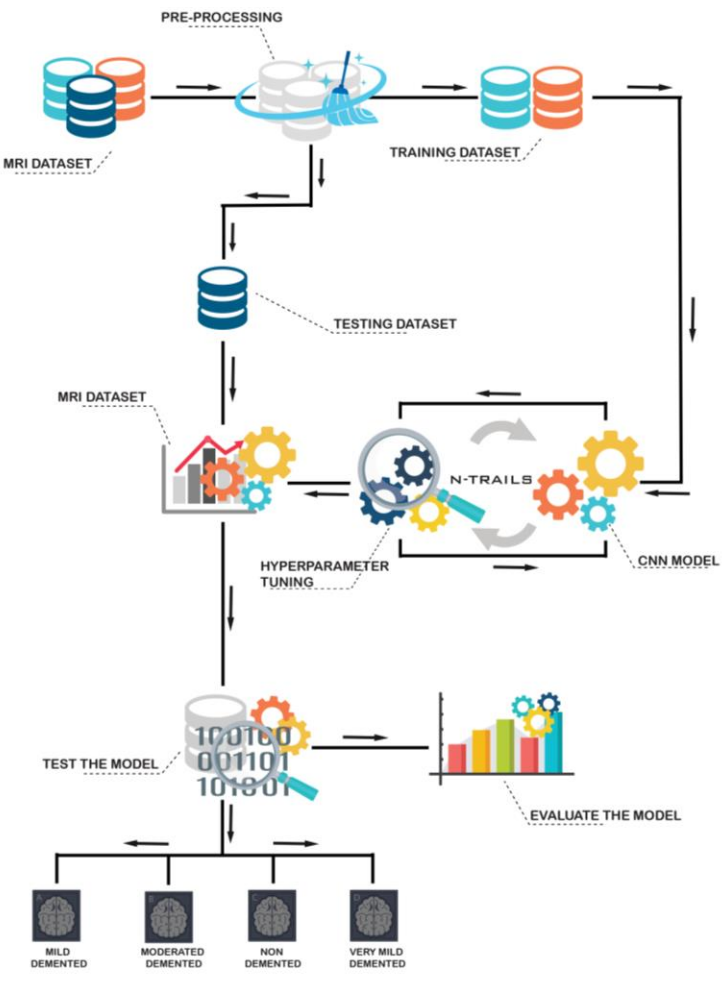

Fig. 1. Flow chart of overall CNN model.

The proposed framework for early detection of Alzheimer's disease is built upon two key components: a Deep Learning detection network and the application of hyperparameter techniques. Let's elaborate on each of these components,

A. *Pre-Processing*

In our project, we employ pre-processing techniques to equalize the datasets for all four classes, ensuring they contain the same amount of data. This step is crucial as it helps us achieve the best accuracy and ensures that each class is equally represented in the dataset. By balancing the number of samples in each class, we create a more robust and unbiased deep learning model. With equal amounts of data for all classes, the model can learn more effectively and make accurate predictions across all categories, making our framework more reliable for early detection of Alzheimer's disease.

TABLE I. INPUT DATASET

Classes Of Alzheimer's Disease Stages	Source Dataset from ADNI	Pre-Processed Dataset	Total
Mild Demented	896	3104	4000
Moderate Demented	64	3936	4000
Non Demented	3200	800	4000
Very Mild Demented	2240	1760	4000

a we utilize data augmentation techniques to address the class imbalance and equalize the datasets for all four classes. Data augmentation involves applying various transformations to the existing data, we include rotations, translations, flips, zooms, and other geometric transformations. Additionally, we can apply random noise or brightness adjustments to enhance the diversity of the data. Augmenting the dataset in this way not only addresses the class imbalance but also helps prevent overfitting and improves the model's generalization ability (All the images are resized into 128 x 128 pixels)

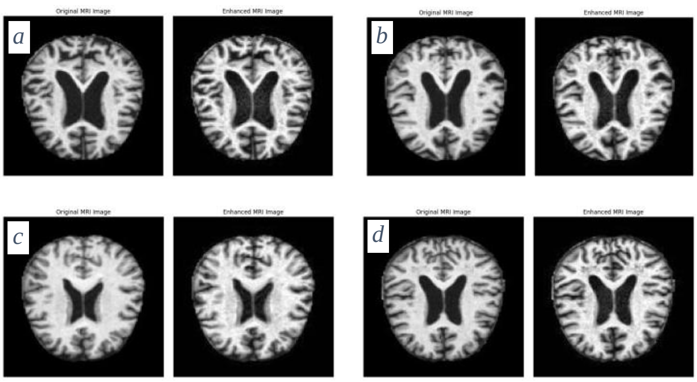

Fig. 2. Original Vs Enhanced MRI of Alzheimer's disease.

A visual example of the proposed pre-processing step to enhance the contrast of MRI images, where figure (a) is Mild Demented (b) is Moderated Demented (c) is Non Demented (d) is Very Mild Demented MRI images with noise removed and enhanced .

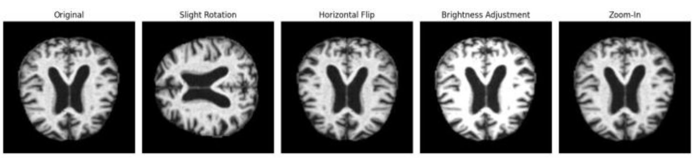

Fig. 3. Original Vs Augmentation MRI images.

In this visualization, we illustrate data augmentation techniques on a single MRI image of a Mild Demented patient. We start with the original image and generate four augmented versions: a slightly rotated image, a horizontally flipped version, a brightness-adjusted variant, and a zoomed-in view. These augmentations provide diverse perspectives, enhancing the dataset for more robust model training and analysis..

By employing data augmentation, we ensure that each class has a similar number of samples, leading to a more accurate and robust deep learning model. This enhanced framework becomes more effective for early detection of Alzheimer's disease, providing better diagnostic capabilities and improving patient outcomes.

B. *Convolutional Neural Networks (CNN)*

In our Convolutional Neural Network (CNN) model, we have leveraged the latest powerful feature extraction capabilities of EfficientNetV2S, which serves as the base model for our architecture. The model's input consists of image data, and we proceed with a series of blocks to extract features and classify the images into one of the four classes.

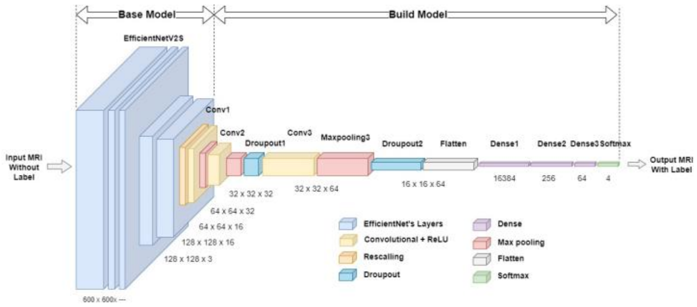

Fig. 4. Strcucture Of CNN Architecture.

In Block 1, we begin with a 2D Convolutional layer, where we apply filters ranging from 16 to 128 with a step of 16. The kernel size is set to 3x3, and we use the Rectified Linear Unit (ReLU) activation function to introduce non-linearity. To maintain spatial dimensions, we employ 'same' padding. Block 2 follows with a 2D Max Pooling layer, using a pool size of 2x2. This step helps reduce the spatial dimensions while retaining the essential features. Block 3 incorporates a Dropout layer with a dropout rate ranging from 0.1 to 0.5 and a step of 0.1. The Dropout layer helps prevent overfitting by randomly dropping out a fraction of neurons during training. In Block 4, we apply another 2D Convolutional layer, similar to Block 1, with the same range of filters, kernel size, activation function, and padding. Block 5 repeats the 2D Max Pooling layer used in Block 2. Block 6 introduces a second Dropout layer, applying the same rate range as in Block 3. In Block 7, we employ a Flatten layer, converting the 2D feature maps into a 1D vector, suitable for further processing in dense layers. Blocks 8 and 9 consist of Dense layers. In Block 8, the number of units varies from 64 to 256 with a step of 32, and we apply the ReLU activation function. Block 9 follows a similar pattern, but the number of units ranges from 32 to 128 with a step of 32. Finally, in Block 10, we use a Dense layer with 4 units, representing the four classes in our classification problem. The activation function for this output layer is Softmax, which provides class probabilities for each input image.

The choice of this architecture, combining EfficientNetV2S as the base model with the custom-defined blocks (Build model) for feature extraction and classification, has been optimized to achieve good classification accuracy. By leveraging the powerful feature representation capabilities of EfficientNetV2S and fine-tuning the blocks to suit our specific problem, we aim to achieve accurate and reliable predictions on our image dataset.

C. *Hyperparameter Tuning*

We have chosen random search as the hyperparameter tuning method from Keras Tuner for our project, primarily because of its efficiency in terms of timing. Random search involves randomly sampling hyperparameter values from predefined ranges, allowing us to explore various combinations without exhaustively searching the entire space. In our tuning process, we will focus on adjusting hyperparameters such as the convolutional filter size, the number of convolutional layers, the number of dense units, the dropout rate, the learning rate, and the batch size. These hyperparameters significantly impact the model's architecture and training process.

To identify the best combination of hyperparameters, we will run the model with 10 different sets of values for each hyperparameter. Each run represents a trial, and we will carefully observe the performance of the model during these trials. After conducting the 10 trials, we will compare the results and select the set of hyperparameters that lead to the highest performance on our validation data.

TABLE II. 10 TRIALS OF HYPERPARAMETER TUNING

Parameter	Trial#1	Trial#2	Trial#3	Trial#4	Trial#5	Trial#6	Trial#7	Trial#8	Trial#9	Trial#10
conv1_filters	48	64	32	64	16	32	32	64	48	32
conv1_kernel	3	5	3	3	5	3	5	5	5	3
conv2_filters	64	96	64	128	32	64	64	128	64	128
conv2_kernel	5	3	5	5	5	3	5	3	5	5
conv3_filters	256	64	192	64	192	256	64	128	128	256
conv1_kernel	5	5	5	5	3	3	3	5	5	3
dropout_1	0.3	0.4	0.2	0.2	0.4	0.3	0.4	0.4	0.2	0.3
dropout_2	0.4	0.4	0.3	0.2	0.3	0.4	0.2	0.4	0.4	0.2
dense_units_1	64	64	256	64	128	256	192	256	192	64
dense_units_2	32	96	96	96	128	128	64	128	64	128
Learning rate	0.01	0.01	0.01	0.001	0.0001	0.0001	0.01	0.001	0.0001	0.0001
validation accuracy	50.08	50.08	50.08	50.08	99.84	99.69	99.84	94.68	99.84	100

IV. RESULTS AND DISCUSSION

A. *Hyperparameter Tuning*

Before hyperparameter tuning, the model already exhibited strong performance on all three datasets: test, validation, and training. The initial results showed a test accuracy 99.22% of the unseen test data. The validation accuracy was 98.59, implying that the model achieved high accuracy on data it had not seen during training. Moreover, during the training phase, the model attained a training accuracy 99.98% of the training data, and it fit the training data closely.

After hyperparameter tuning, the model's performance further improved, showcasing the effectiveness of the chosen hyperparameters. The test accuracy increased to 99.84%. The validation accuracy also improved significantly to 100%. During the training phase, the model achieved a perfect training accuracy of 100%, meaning it accurately predicted all the training data, achieving optimal fit to the training set.

The significant improvement in testing, validation, and training metrics after hyperparameter tuning demonstrates the importance of selecting optimal hyperparameters for the model. By fine-tuning the hyperparameters, the model's performance was boosted, leading to better generalization, higher accuracy, and lower losses on unseen and validation data. The tuning process helped the model find the best configuration, resulting in a more robust and accurate model for the given task.

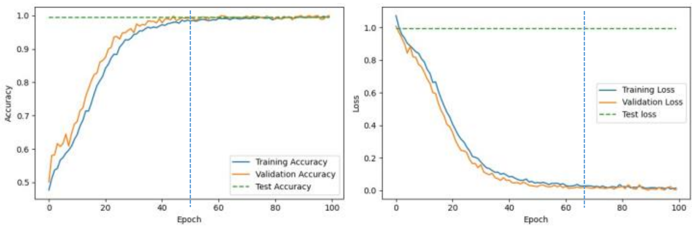

Fig. 5. Loss and Accuracy plot. (*Before Tuned CNN model*)

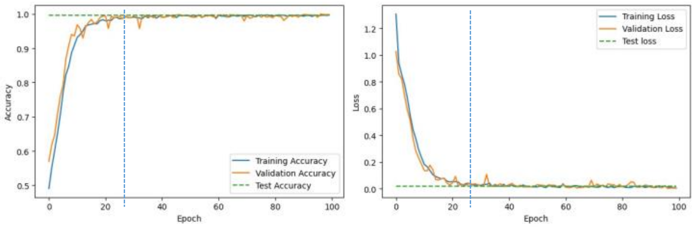

Fig. 6. Loss and Accuracy plot. (*After Tuned CNN model*)

according to two graphs Stable points of achieving the best accuracy and minimal loss are effectively attained after hyperparameter tuning in the CNN model.

Here is the table containing the accuracy and losses for the test, training, and validation datasets.

TABLE III. ACCURACY AND LOSS FOR CNN MODEL

	Before Tuned	After Tuned
Test Accuracy	99.22	99.84
Validation Accuracy	98.59	100
Train Accuracy	99.98	100
Test Loss	2.46	0.93
Validation Loss	3.48	0.00
Train Loss	0.07	0.00

The significant improvement in testing, validation, and training metrics after hyperparameter tuning demonstrates the importance of selecting optimal hyperparameters for the model. By fine-tuning the hyperparameters, the model's performance was boosted, leading to better generalization, higher accuracy, and lower losses on unseen and validation data. The tuning process helped the model find the best configuration, resulting in a more robust and accurate model for the given task.

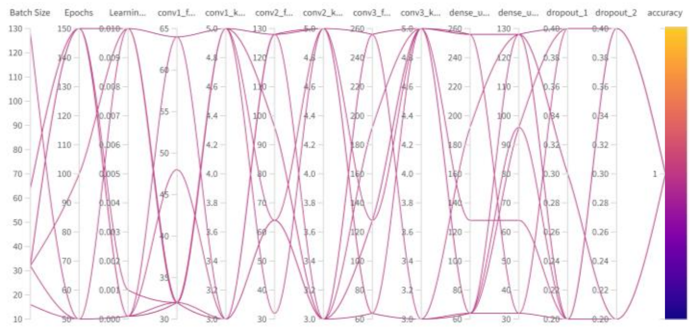

Fig. 7. Parallel Coordinates Plot Visualizing the Performance of 10 trials Over a Set Number of Hyperparameters

B. Datasets

TABLE IV. ACCURACY AND LOSS FOR CNN MODEL

Number of MRIs		Without Pre-Processing				With Pre-Processing
Input	Mild Demented	224	448	672	896	4000
	Moderated Demented	16	32	48	64	4000
	Non Demented	800	1600	2400	3200	4000
	Very Mild Demented	560	1120	1680	2240	4000
	Total	1 600 (25%)	3 200 (50%)	4 800 (75%)	6 400 (100%)	16 000
Accuracy	Train accuracy	100	100	99.55	99.89	99.89
	Validation accuracy	88.33	91.21	95.41	98.59	99.84
	Test accuracy	88.76	90.12	95.02	99.22	99.32

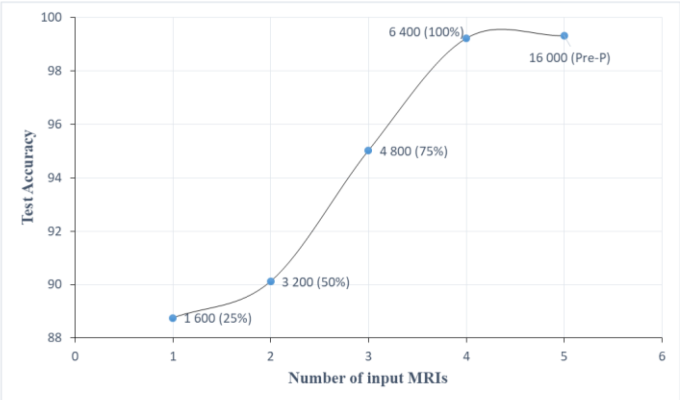

Fig. 8. Accuracy Change With Dataset With and Without Pre-Processing

While we Increasing the size of the input dataset to our CNN model improve model accuracy by providing more examples for learning, enhancing generalization to unseen data, reducing biases, and enabling better feature representations. However, the benefits may saturate beyond a certain point, and extremely large datasets may require substantial computational resources. In summary, larger datasets generally lead to better model performance and robustness.

But we Increasing data using pre-processing techniques can initially lead to significant accuracy improvements by providing more diverse examples and improving generalization. However, as the dataset grows larger, the rate of accuracy improvement may decrease since the model becomes more familiar with the existing data and the impact of augmented samples diminishes relative to the original data. Nonetheless, data augmentation remains essential for preventing overfitting and enhancing the model's robustness.

C. CNN Architecture

TABLE V. ACCURACY AND LOSS FOR CNN MODEL

Accuracy/loss	Without additional layers	With additional layers
Test Accuracy	85.53	99.84
Validation Accuracy	88.22	100
Train Accuracy	98.98	100
Test Loss	9.46	0.93
Validation Loss	8.48	0.00
Train Loss	0.17	0.00

EfficientNetV2S is a highly efficient and powerful convolutional neural network architecture, known for its state-of-the-art performance while being computationally efficient. However, in certain scenarios, it might be beneficial to enhance the model further by introducing additional layers. By adding extra convolutional layers, such as conv1_filters, conv1_kernel, conv2_filters, conv2_kernel, and conv3_filters, we can increase the model's capacity to capture intricate features from the dataset. Furthermore, applying dropout layers after each set of convolutional layers (dropout_1 and dropout_2) helps in regularizing the model, preventing overfitting, and promoting better generalization. Additionally, by adjusting the number of units in the dense layers (dense_units_1 and dense_units_2), we can fine-tune the model's ability to learn complex representations and improve its overall performance.

TABLE VI. ACCURACY, LOSS AND EXECUTION TIME CHANGE WITH CNN ARCHITECTURE

CNN Architecture	Accuracy	Loss	Execution Time Per Step (ms)
rasnet 101	99.69	0.76	8ms
rasnet 101	99.07	2.75	8ms
LeNet-5	98.75	4.59	8ms
VGG16	99.07	2.37	8ms
VGG19	99.53	1.92	8ms
InceptionV3	99.53	1.72	8ms
InceptionResNetV2	99.38	3.38	8ms
AlexNet	99.22	3.28	8ms
EfficientNetB0	99.69	1.28	12ms
EfficientNetB1	98.75	4.98	12ms
EfficientNetB2	99.53	0.97	1s 12ms
EfficientNetB3	98.91	2.27	1s 14ms
EfficientNetB4	99.38	1.46	13ms
EfficientNetB5	98.91	3.14	13ms
EfficientNetB6	99.69	0.87	12ms
EfficientNetB7	99.53	0.122	8ms
EfficientNetV2B0	99.22	1.37	1s 12ms
EfficientNetV2B1	99.69	1.37	1s 12ms
EfficientNetV2B2	99.38	1.1	1s 14ms
EfficientNetV2B3	99.22	1.81	1s 12ms
EfficientNetV2S	99.84	0.55	12ms
EfficientNetV2M	99.22	2.32	1s 13ms
EfficientNetV2L	99.07	2.09	1s 12ms

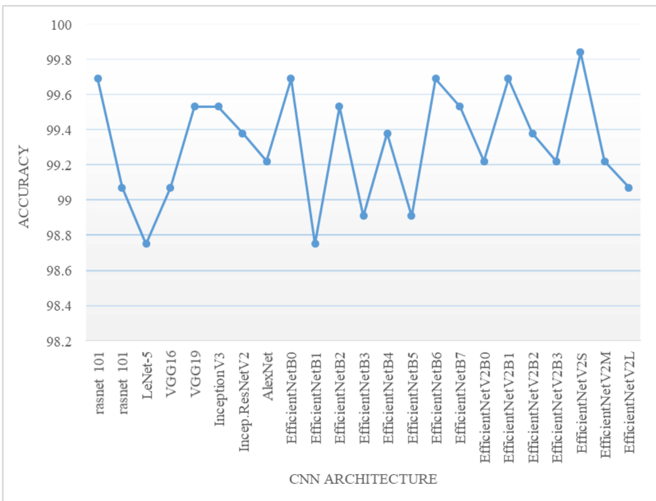

Fig. 9. Accuracy Change With Types of CNN Architecture.

Among popular CNN architectures, there are variations in execution time, accuracy, and loss. However, EfficientNet stands out as the best choice overall for several reasons. Firstly, it incorporates the latest advancements in deep learning, making it highly advanced and effective. Secondly, EfficientNet offers a wide range of model sizes (B0-B7 (V1), B0-B3(V2), V2S, V2M, V2L) that cater to different computational resources, ensuring optimal efficiency. Thirdly, its compound scaling approach efficiently balances accuracy and computational performance. Fourthly, EfficientNet consistently achieves state-of-the-art results on benchmark datasets like ImageNet, highlighting its superior performance. Lastly, it employs innovative features such as mobile inverted bottleneck (MBConv) blocks and squeeze-and-excitation (SE) blocks, contributing to its expressive power and efficiency. As a result, EfficientNet emerges as the best choice for various computer vision tasks, offering exceptional accuracy and resource efficiency.

D. Epoch

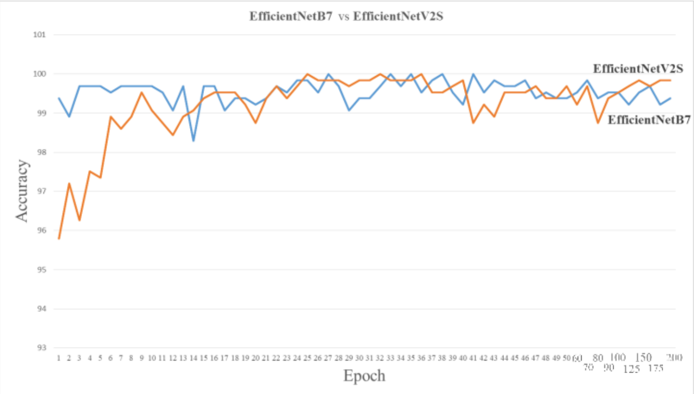

Fig. 10. Accuracy Change With Epoch.

While we increases epoch from 0 to 200 during model training, the accuracy generally rises initially. However, after reaching its peak around 100 epochs, the accuracy may start to decline. This behavior can be observed due to the dynamics of the learning process.

During the early epochs, the model learns from the training data and gradually improves its performance. As a result, the accuracy on both the training and validation datasets increases. Around the midpoint (around 100 epochs), the model reaches its highest validation accuracy, indicating that it generalizes well to new data.

However, as the training continues beyond this point, the model may start to overfit. Overfitting occurs when the model becomes too specialized in the training data and performs poorly on new, unseen data. As a result, the training accuracy keeps improving, but the validation accuracy starts to decline or stabilize.

This phenomenon highlights the trade-off between model complexity and generalization. Finding the optimal number of epochs is crucial to prevent overfitting and ensure the model's ability to generalize effectively. Techniques like early stopping can be employed to stop training when the validation accuracy stops improving, helping to identify the best model without overfitting.

E. Batch size

In our analysis of various batch sizes (8, 16, 32, 64, 128, 256, 512, 1024, and 2048) for training our deep learning model, we discovered that a batch size of 64 yielded the highest accuracy in Alzheimer's disease stage detection. This batch size achieved the optimal balance between stability and adaptability, resulting in the best performance. Additionally, we observed that smaller batch sizes led to faster execution times, but they did not perform as well in terms of accuracy. On the other hand, larger batch sizes had longer execution times but offered more stable training updates. Considering both accuracy and execution time, a batch size of 64 emerged as the most suitable choice for our model.

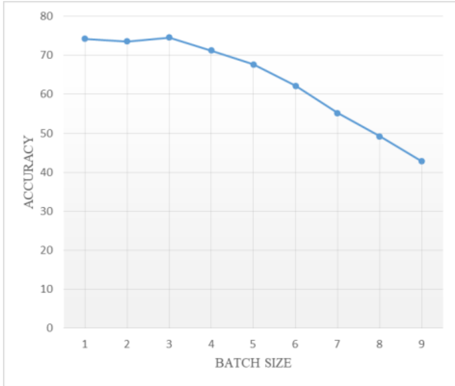

Fig. 11. Accuracy Change With Epoch.

V. CONCLUSION

Alzheimer's disease (AD) is a progressive neurodegenerative disorder that affects a significant portion of the elderly population, and its early and accurate diagnosis is crucial for effective management and treatment. In recent years, various state-of-the-art methods leveraging advanced technologies such as deep learning, machine learning, neuroimaging, and natural language processing have been explored for AD diagnosis. These methods have shown promising results in improving accuracy, early detection, and effective management of the disease.

In this research, we aimed to address the limitations of traditional diagnostic approaches by focusing on deep learning object detection methods for AD diagnosis. We conducted comprehensive comparisons and explored various techniques, including hyperparameter tuning, to identify the most effective approach for solving this challenging diagnostic problem.

Our study introduced the utilization of hyperparameter tuning in our CNN model, allowing us to identify the best parameter configurations that yield optimal accuracy while considering execution time. By comparing various hyperparameter techniques, such as Grid Search, Random Search, Bayesian Optimization, Genetic Algorithms, Sequential Model-Based Optimization (SMBO), and Gradient-Based Optimization, we were able to select the most efficient approach for our model. Additionally, we evaluated the performance of different CNN architectures, including EfficientNet, ResNet50, VGG16, InceptionV1, and AlexNet, and compared their accuracy, loss, and execution time. We also examined the impact of dataset size and augmentation techniques on the model's performance, as well as the effects of different types of hyperparameter tuning and batch sizes on the model's accuracy and execution time.

By incorporating the latest techniques and leveraging the EfficientNetV2S architecture version 2 in our CNN model, we achieved significant improvements in Alzheimer's disease stage detection. Our model serves as a benchmark for deep learning-based AD diagnosis, categorizing individuals into four stages: Mild Demented, Moderate Demented, Non Demented, and Very Mild Demented. The utilization of the ADNI dataset through Kaggle, with its diverse MRI data, allowed us to extract meaningful features and patterns associated with Alzheimer's disease pathology. This research contributes to the advancement of diagnostic tools and therapeutic interventions, ultimately enhancing the understanding and management of Alzheimer's disease.

In conclusion, our research demonstrates the potential of deep learning-based techniques for Alzheimer's disease diagnosis. By fine-tuning hyperparameters and selecting optimal model architectures, we were able to achieve remarkable accuracy and performance in detecting the stages of Alzheimer's disease. This work represents a significant step forward in the field of Alzheimer's disease diagnosis and has the potential to aid in the development of more accurate and reliable diagnostic tools and treatment strategies for this debilitating condition. Further research and exploration in this area will continue to advance the understanding and management of Alzheimer's disease, ultimately leading to improved patient outcomes and quality of life for those affected by this condition.

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