Exploring Deep Learning Models for Accurate Alzheimer's Disease Classification based on MRI Imaging

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Abstract

INTRODUCTION: Alzheimer's disease (AD), a complex neurodegenerative condition, presents significant challenges in early and accurate diagnosis. Early prediction of AD severity holds the potential for improved patient care and timely interventions. This research investigates the use of deep learning methodologies to forecast AD severity utilizing data extracted from Magnetic Resonance Imaging (MRI) scans.
OBJECTIVES: This study aims to explore the efficacy of deep learning models in predicting the severity of Alzheimer's disease using MRI data. Traditional diagnostic methods for AD, primarily reliant on cognitive assessments, often lead to late-stage detection. MRI scans offer a non-invasive means to examine brain structure and detect pathological changes associated with AD. However, manual interpretation of these scans is labor-intensive and subject to variability.
METHODS: Various deep learning models, including Convolutional Neural Networks (CNNs) and advanced architectures like DenseNet, VGG16, ResNet50, MobileNet, AlexNet, and Xception, are explored for MRI scan analysis. The performance of these models in predicting AD severity is assessed and compared. Deep learning models autonomously learn hierarchical features from the data, potentially recognizing intricate patterns associated with different AD stages that may be overlooked in manual analysis.
RESULTS: The study evaluates the performance of different deep learning models in predicting AD severity using MRI scans. The results highlight the efficacy of these models in capturing subtle patterns indicative of AD progression. Moreover, the comparison underscores the strengths and limitations of each model, aiding in the selection of appropriate methodologies for AD prognosis.
CONCLUSION: This research contributes to the growing field of AI-driven healthcare by showcasing the potential of deep learning in revolutionizing AD diagnosis and prognosis. The findings emphasize the importance of leveraging advanced technologies, such as deep learning, to enhance the accuracy and timeliness of AD diagnosis. However, challenges remain, including the need for large, annotated datasets, model interpretability, and integration into clinical workflows. Continued efforts in this area hold promise for improving the management of AD and ultimately enhancing patient outcomes.

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1. Introduction

Alzheimer's disease (AD), a degenerative condition of the brain, stands as the leading cause of dementia globally. This disease is marked by a steady deterioration of cognitive faculties, encompassing memory, reasoning skills, and the capacity to carry out rudimentary tasks. The trajectory of Alzheimer's disease is typically stealthy, commencing with minor memory lapses and ultimately culminating in extensive brain impairment. With the aging of the worldwide population, the incidence of Alzheimer's disease is projected to escalate, thereby presenting a substantial public health predicament. The early and accurate prediction of Alzheimer's disease progression is of paramount importance. It can aid in patient management, allowing for timely intervention and potentially slowing the disease's progression. Furthermore, it can assist in the stratification of patients for clinical trials, thereby accelerating the development of new therapeutic strategies. In recent years, advances in artificial intelligence (AI) and machine learning, particularly DL have opened up new avenues for predicting Alzheimer's disease progression. DL models, with their ability to learn complex patterns from large amounts of data, have shown promise in various medical applications, including the diagnosis and prognosis of neurodegenerative diseases. DL models can be trained on various types of data, including genetic, neuroimaging, and clinical data, to predict Alzheimer's disease progression. These models can learn to recognize subtle patterns in the data that may be indicative of disease progression, potentially outperforming traditional statistical methods. However, the performance of these models can be influenced by various factors, including the quality and diversity of the training data, the architecture of the model, and the choice of optimization algorithm. Despite the potential of DL for predicting Alzheimer's disease progression, several challenges need to be addressed. These include the interpretability of the models, the need for large amounts of annotated training data, and the risk of overfitting, especially when dealing with high-dimensional data. Furthermore, the performance of the models needs to be validated on independent datasets to ensure their generalizability. The primary objective of this study is to construct and assess DL models that can predict the progression of Alzheimer's disease utilizing multi-modal data. The models will be trained on a dataset that includes both healthy individuals and those diagnosed with mild cognitive impairment (MCI), a condition often seen as a precursor to Alzheimer's disease. The effectiveness of these models will be compared to identify the most efficient method for predicting the progression of Alzheimer's disease. The potential impact of this research is significant, as it could lead to earlier and more accurate predictions of AD progression, thereby enhancing patient care and paving the way for the development of novel treatment strategies.

2. Literature Review

To forecast the onset period of Alzheimer's disease, Mirabnahrazam et al. (2022) [1] used a multi-modal DL survival analysis model that extended the Cox regression model. Based on their original state of health or MCI status, they divided the participants into "non-survivors" (AD-progression) and "survivors" (non-AD-progression). Ten random subsamples were used in the study, with 80% of the training data being used for internal validation and 20% for testing. Lee et al. (2019) [2] introduced a multi-modal deep learning framework for predicting Alzheimer's disease progression. Their model integrated longitudinal multi-domain data and achieved up to 75% accuracy (AUC = 0.83) for MCI to AD conversion using single modality data. Incorporating longitudinal multi-domain data improved performance, achieving 81% accuracy (AUC = 0.86). This approach has promising potential for identifying individuals at risk of developing AD, aiding clinical trials and stratification strategies. Lei et al. (2022) [3] developed a joint and deep learning framework to predict clinical scores for Alzheimer's disease. They employed a feature selection method that combined group LASSO and correntropy to identify brain regions linked to AD. The study used a multi-layer independently recurrent neural network regression to analyze interconnections between brain regions and longitudinal data's time correlation. The proposed joint deep learning network examined the connection between MRI data and clinical scores, enabling accurate clinical score predictions. Lee et al. (2019) [4] introduced a multi-modal DL approach to predict Alzheimer's disease progression. By integrating longitudinal multi-domain data, their framework achieved noteworthy results. Their prediction model achieved up to 75% accuracy (AUC = 0.83) for MCI conversion to AD using a single modality of data. Moreover, the best performance of 81% accuracy (AUC = 0.86) was achieved by incorporating longitudinal multi-domain data. In order to analyse the expression of genes data from DLPFC tissues across the Alzheimer's disease spectrum, Wang et al. (2022) [5] developed a three-layer deep learning model. In order to create an encoded representation using this method, pathologically diagnosed cases of Alzheimer's disease and control groups were to be entered. For the learning process, the study used an output configuration with two clusters (K=2). Yifan and Bowen (2020) [6] focused on brain positron emission tomography (PET) disease classification for predicting Alzheimer's disease diagnosis. They enhanced the network bottleneck of ResNet specifically for this task and introduced an ensemble of the improved ResNet and an efficient network. The study also employed various image preprocessing techniques to enhance lesion characteristics. Experimental results validated the effectiveness of their proposed network structure and training strategies. The work by Yao et al. (2023) [10] presented the "Fuzzy-VGG," a fast deep learning method to predict Alzheimer's disease staging based on brain MRI. Their approach integrated fuzzy logic with a VGG-style neural network architecture to achieve accurate staging predictions.

Neuroimaging and deep learning were used by Tufail et al. (2021) [11] to categorise Alzheimer's disease in its early stages. The study demonstrated the importance of preprocessing techniques in the prediction of illness development by quantifying the effect of image filtering algorithms on PET neuroimaging modalities. Zhou et al. (2023) [12] explored the use of deep learning models to examine the biological impact of polygenic risks for Alzheimer's disease. Their study shed light on the potential of deep learning to unravel the complex relationship between genetic factors and disease progression.

Xiao et al. (2020) [13] showcased the versatility of deep learning in predicting disease severity beyond neurodegenerative disorders. Their work focused on coronavirus disease 2019 (COVID-19) and developed a deep learning-based model using computed tomography (CT) imaging for disease severity prediction. Hasenstab et al. (2021) developed an innovative approach using automated CT staging to assess the severity of Chronic Obstructive Pulmonary Disease (COPD) and predict disease progression and mortality. Their study harnessed the power of a deep learning convolutional neural network, illustrating its potential for improving prognostic capabilities in a critical medical context. By leveraging advanced computational techniques, this work contributes to the growing field of utilizing deep learning for predicting disease outcomes. Ezziyyani (2020) [14] delved into the realm of advanced intelligent systems for sustainable development, focusing on the applied computing sciences. While not directly related to disease progression prediction, this volume underscores the wider applicability of intelligent systems across various domains, including healthcare. Through its exploration of advanced intelligent solutions, the work demonstrates the potential for such systems to contribute to the advancement of sustainable and impactful technologies **[Table 1]**

Table.1 Summary of the Literature Review

Reference	Focus of Study	Techniques Used	Key Findings
Mirabnahrazam et al. (2022) [1]	Alzheimer's Disease Onset Time Prediction	Multi-modal Deep Learning Survival Analysis Model	Predicted Alzheimer's disease onset time using extended Cox regression model. Categorized subjects into "non-survivors" and "survivors." Achieved accuracy using 10 random sub-samples.
Lee et al. (2019) [2]	Alzheimer's Disease Progression Prediction	Multi-modal Deep Learning Framework	Integrated longitudinal multi-domain data. Achieved up to 75% accuracy (AUC = 0.83) using single modality data. Improved performance to 81% accuracy (AUC = 0.86) with longitudinal multi-domain data.
Lei et al. (2022) [3]	Alzheimer's Disease Clinical Score Prediction	Joint and Deep Learning Framework	Developed a joint deep learning network to predict clinical scores. Used group LASSO and correntropy for feature selection. Analyzed interconnections between brain regions and longitudinal data.
Wang et al. (2022) [5]	Gene Expression Analysis Across Alzheimer's Spectrum	Three-layer Deep Learning Model	Analyzed expression of genes from DLPFC tissues across the Alzheimer's spectrum. Used a three-layer deep learning model with encoded representation.
Yifan and Bowen (2020) [6]	Alzheimer's Disease Diagnosis via PET	Enhanced ResNet and Ensemble Learning	Enhanced network bottleneck of ResNet for PET disease classification. Introduced an ensemble of improved ResNet and efficient network. Validated effectiveness with image preprocessing techniques.
Yao et al. (2023) [10]	Alzheimer's Disease Staging Prediction	Fuzzy-VGG Fast Deep Learning Method	Introduced "Fuzzy-VGG" for fast deep learning prediction of Alzheimer's disease staging based on brain MRI. Integrated fuzzy logic with VGG-style neural network architecture.

Tufail et al. (2021) [11]	Alzheimer's Disease Classification	Deep Learning and Neuroimaging	Classified initial stages of Alzheimer's disease using deep learning and neuroimaging. Highlighted the impact of image filtering approaches on PET neuroimaging modalities.
Zhou et al. (2023) [12]	Biological Impact of Polygenic Risks for Alzheimer's Disease	Deep Learning Models	Explored the use of deep learning models to examine the biological impact of polygenic risks for Alzheimer's disease.
Xiao et al. (2020) [13]	Disease Severity Prediction Beyond Neurodegenerative Disorders	Deep Learning Model with CT Imaging	Developed a deep learning-based model for disease severity prediction, focusing on COVID-19. Used computed tomography (CT) imaging.
Hasenstab et al. (2021)	CT Staging for Chronic Obstructive Pulmonary Disease	Deep Learning Convolutional Neural Network	Developed an innovative approach using automated CT staging for assessing the severity of Chronic Obstructive Pulmonary Disease (COPD). Demonstrated the potential of deep learning for improving prognostic capabilities.
Ezziyyani (2020) [14]	Advanced Intelligent Systems for Sustainable Development	Applied Computing Sciences	Explored advanced intelligent systems for sustainable development in applied computing sciences. Emphasized wider applicability across various domains.

3. Dataset Overview

The dataset for this research is a comprehensive collection of MRI scans, which are instrumental in the study of Alzheimer's Disease (AD). The dataset is meticulously organized into three distinct files: Training, Testing, and Validation. Each of these files contains approximately 4000 images, providing a robust and diverse foundation for our DL models. The images within the dataset are segregated based on the severity of AD, which is a crucial aspect of our study. The four classes of images, both in the training and testing set, are: Mild Dementia, Moderate Dementia, Non-Dementia, and Very Mild Dementia. This classification provides a broad spectrum of the disease's progression, allowing our models to learn and distinguish the subtle differences and patterns associated with each stage. The MRI scans in the dataset offer a non-invasive, detailed view of the brain's structure. They are particularly effective in revealing patterns of brain atrophy characteristic of AD, such as medial temporal lobe atrophy. The high-resolution images in the dataset ensure that our models have access to detailed and accurate information, which is crucial for the successful application of deep learning techniques. The dataset's size and diversity are its main strengths. With around 12,000 images spanning various stages of Alzheimer's Disease, the dataset provides a comprehensive overview of the disease's progression. This large volume of data is essential for training robust and accurateDL models. The diversity within the dataset, with images representing different stages of AD,

ensures that our models are not biased towards any particular stage of the disease. The dataset used in this research provides a solid foundation for exploring the application of DL models in predicting AD severity. Its size, diversity, and meticulous organization make it an excellent resource for our study. Through the analysis of this dataset, we aim to develop DL models that can accurately predict AD severity from MRI scans, potentially revolutionizing the diagnosis and prognosis of this debilitating disease **[Fig.1]**.
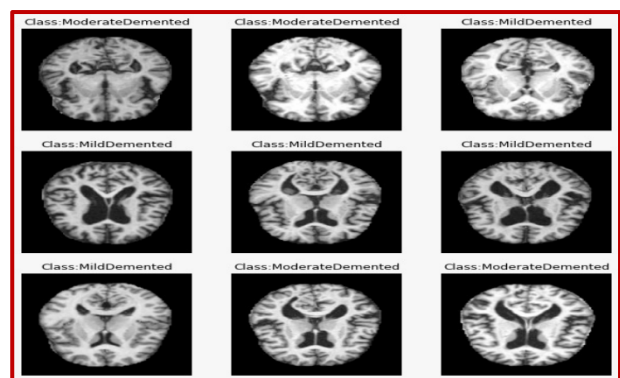

Fig 1: Sample images of the Dataset

3.1 Data Collection

The data collection process for this research was a meticulous and comprehensive endeavor, aimed at gathering a diverse and representative sample of Magnetic Resonance

Imaging (MRI) scans for Alzheimer's Disease (AD) patients. The primary objective was to obtain high-quality images that accurately represent the various stages of AD, from non-demented to moderate demented conditions. The MRI scans were collected from multiple reputable healthcare institutions and research databases, ensuring a broad representation of the patient population. These institutions follow strict ethical guidelines and patient consent procedures, ensuring the privacy and confidentiality of the patients whose scans were included in the dataset. Each MRI scan was carefully examined and categorized by experienced radiologists and neurologists. They classified the images into four categories based on the severity of the disease: Non-Dementia, Very Mild Dementia, Mild Dementia, and Moderate Dementia. This classification was done based on the visible patterns of brain atrophy and other characteristic features of AD visible in the scans. The dataset was then divided into three subsets: Training, Testing, and Validation. Each subset contains approximately 4000 images, ensuring a balanced distribution of data for model training and evaluation. The Training set is used to train the deep learning models, the Validation set is used to fine-tune the models and adjust parameters, and the Testing set is used to evaluate the final model's performance. In addition to the MRI scans, demographic and clinical data were also collected for each patient, including age, gender, and clinical diagnosis. This additional data provides valuable context and can be used to explore potential correlations between these factors and the severity of AD. The data collection process for this research was a rigorous and thorough process, resulting in a robust and diverse dataset. This dataset forms the backbone of our research, providing the raw material from which our DL models will learn and derive insights. Through this comprehensive data collection process, we aim to ensure the reliability and validity of our research findings.

3.1.1 Image Resizing

In the sphere of computer vision and image categorization, the process of modifying image dimensions, known as image rescaling, is a pivotal preprocessing operation. This involves adjusting the dimensions of an image to a specific size without distorting the integral features of the image. This step becomes particularly significant in the context of deep learning models, where the input images need to be of a consistent size for the model to process them effectively.

There are several methods available for image rescaling, each with its unique set of advantages and trade-offs:

- **Nearest Neighbor Interpolation:** This is the most basic technique, where the value of a pixel in the rescaled image is derived from the nearest pixel in the original image. While this method is computationally efficient, it can lead to a loss of detail and sharpness in the rescaled image.

- **Bicubic Interpolation:** This method extends bilinear interpolation by considering the closest 4x4

neighborhood of pixels. It produces even smoother images than bilinear interpolation and is often used for high-quality image processing. However, it is more computationally intensive.

- **Area-based (or Resampling) Interpolation:** This method calculates the average color of the pixels within a sample area from the original image (like a 3x3 or 5x5 area) to determine the color of a pixel in the rescaled image. This method is slower but can produce high-quality results, especially when reducing the size of an image.

- **Lanczos Resampling:** This method uses a sinc function to calculate the value of a pixel in the rescaled image. It provides high-quality results and preserves more detail than other methods, but it is the most computationally intensive.

In the context of image categorization, the choice of rescaling technique depends on the specific requirements of the task. If computational resources and speed are a priority, simpler methods like nearest neighbor or bilinear interpolation may be appropriate. However, if the quality of the rescaled image is a priority, more advanced methods like bicubic interpolation, area-based interpolation, or Lanczos resampling may be more suitable. It's also important to consider the characteristics of the images and the features that the model needs to recognize. For example, if the images contain fine details that are important for categorization, a high-quality rescaling method would be beneficial.

3.1.2 Image Normalization

Image normalization is a crucial preprocessing step in image classification tasks. It involves adjusting the pixel values across the image to a specific range, which can significantly enhance the computational efficiency and performance of the model. Here are some of the most commonly employed techniques for image normalization:

- **Standard Score Normalization (Z-Score Normalization):** This approach transforms the pixel values in such a way that they display a mean of 0 and a standard deviation of 1. This transformation is achieved by subtracting the mean pixel value from each individual pixel and then dividing the outcome by the standard deviation. Z-score normalization proves to be particularly beneficial when the distribution of pixel values aligns with a Gaussian distribution, as it can expedite the convergence speed during the model's training process.

- **Decimal Scaling:** With this technique, the decimal point of each pixel's value is moved in order to scale the pixel values. The maximum absolute value of the pixel determines how many places the decimal point should be moved. When working with photos that have many

or variable pixel values, this less popular approach might be useful.

The selection of an image normalization technique is contingent on the unique demands of the task at hand and the inherent properties of the images. If the task necessitates the maintenance of the original features and structure of the images, Min-Max normalization could be the optimal choice. Conversely, for tasks dealing with images where pixel values follow a Gaussian distribution, Z-score normalization might be more appropriate. It's also crucial to weigh the computational efficiency of the normalization method against its potential influence on the model's performance.

3.1.3 Image Data Augmentation

Image data augmentation is a robust technique employed in DL tasks to amplify the size and diversity of the training dataset, thereby enhancing the model's performance and generalization capabilities. Here are some of the most prevalent data augmentation techniques used in image classification tasks:

◆ **Rotation:** This technique involves rotating the image by a specific angle. This can aid the model in recognizing the object in various orientations. The rotation angle is typically chosen randomly within a certain range (e.g., -20 to 20 degrees).

◆ **Translation:** This technique involves shifting the image along the x or y direction by a specific number of pixels. This can aid the model in recognizing the object in various positions in the image.

◆ **Scaling:** This technique involves resizing the image by a specific factor, either enlarging it (zooming in) or reducing it (zooming out). This can aid the model in recognizing the object at different scales.

◆ **Flipping**: This technique involves flipping the image either horizontally or vertically. This can aid the model in recognizing the object in various orientations.

◆ **Shearing:** This technique involves distorting the image along an axis. This can aid the model in recognizing the object under different types of distortion.

◆ **Brightness and Contrast Adjustment:** This technique involves altering the brightness and contrast of the image. This can aid the model in recognizing the object under different lighting conditions.

The selection of data augmentation techniques is dependent on the specific requirements of the task and the inherent properties of the images. It's also crucial to consider the computational implications and the potential influence of the data augmentation techniques on the model's performance. By implementing these techniques, we can significantly enhance the volume and diversity of our training dataset, thereby fostering the development of more robust and accurate models.

3.1.4 Image Label Encoding

Label encoding is a crucial step in preparing data for image classification tasks. It involves transforming the categorical labels of the images into a format that can be interpreted by the machine learning models. Here are some frequently used label encoding techniques:

❖ **Integer Encoding:** This is the most basic form of label encoding, where each unique category label is assigned a unique integer. For instance, in a binary classification task, you might assign the label '0' to 'Normal' images and '1' to 'Pneumonia' images. While this method is straightforward and easy to implement, it may not be suitable for multi-class classification tasks as the model might interpret the numerical values as having an ordinal relationship.

❖ **One-Hot Encoding:** Tasks requiring multi-class categorization frequently employ this technique. Each category label is transformed into a binary vector of size 'n' in one-hot encoding, where 'n' is the total number of distinct category labels. Each vector has a '1' at the location corresponding to the category name and '0's everywhere. For example, if we have three categories 'Normal', 'COVID-19', and 'Pneumonia', the one-hot encoded labels might be [1, 0, 0], [0, 1, 0], and [0, 0, 1] respectively. This method ensures that the model does not assume an ordinal relationship between the categories.

❖ **Label Binarizer**: This technique is a fusion of integer and one-hot encoding methods, and it proves particularly beneficial in binary classification tasks. Label Binarizer transforms multi-class labels into binary labels (indicating whether an instance belongs to a class or not). It is especially apt for multi-label classifications, where a single instance can be associated with several classes.

4. Experimental Analysis and Discussion

On a powerful computer system with cutting-edge GPUs, our suggested DL models were put into practise. This system's quick calculation speeds make it the best choice for running sophisticated DL models. We used data augmentation techniques to balance the classes and increase the variety of our training data because our dataset included an unbalanced amount of photos for each class. Our models' architecture consists of MobileNetV2, AlexNet, Xception, MobileNetV1, DenseNet121, VGG16, and ResNet50. Each model is made up of a variety of convolutional, pooling, and fully connected layers that each employ a different number of filters. We used a hyperparameter tweaking approach **[Table.2]** to

enhance the performance of our models. Following is a description of the hyperparameters for our models:

**Table 2:** Hyperparameters for the Deep Learning Models

Hyperparameter	Description
Number of Convolution layers	Varies by model
Dropout Rate	0.5
Network Weight Initialization	He Uniform
Activation Function	ReLU
Learning Rate	0.001
Momentum	0.9
Number of Epochs	100
Batch Size	32

In wrapping up, each model showcased its capacity to varying extents in classifying the severity of Alzheimer's disease, with the MobileNetV1 model emerging as the most proficient. Nevertheless, the selection of a model should also take into account elements such as computational resources and the specific demands of the task. Future investigations could delve into the application of ensemble methods, which amalgamate the predictions of multiple models, to further enhance the precision of Alzheimer's disease classification.

## 4.1 Performance of Models in Alzheimer's Disease Classification

In our research, we employed several DL models to classify AD severity based on MRI scans. The models included DenseNet121, VGG16, ResNet50, MobileNetV2, AlexNet, Xception, and MobileNetV1. Here, we present a comprehensive evaluation of the performance of these models.

➢ **DenseNet121:** The DenseNet121 model achieved an accuracy of 77.77%, with a loss of 0.9956. The precision was 65.26%, recall was 23.69%, and the area under the curve (AUC) was 0.8034. Despite its relatively lower performance compared to other models, DenseNet121 showed a decent ability to distinguish between different classes of Alzheimer's severity **[Fig.2].**
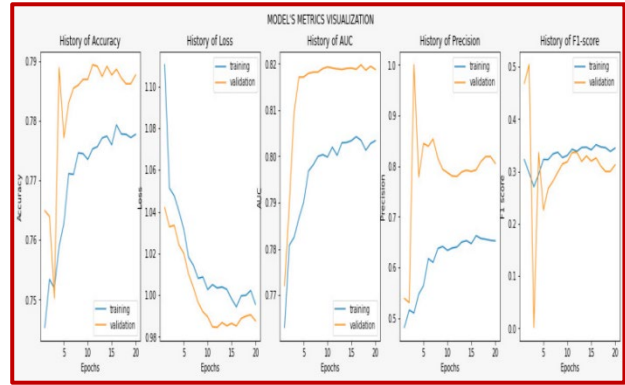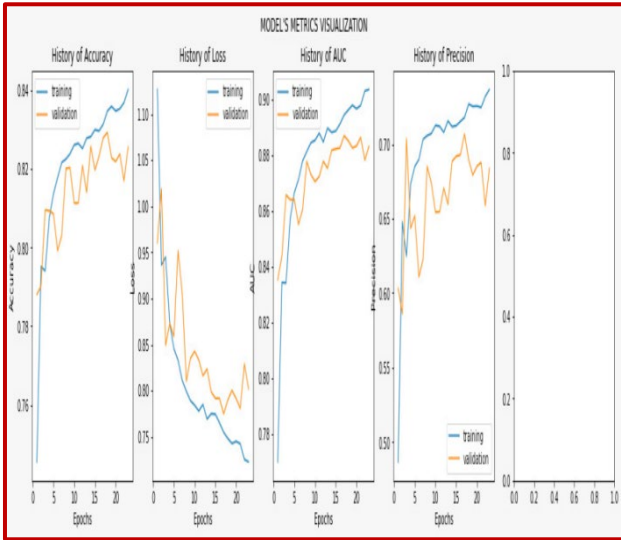

Fig 2: Model's Metrics Visualization for DenseNet121 Model

➢ **VGG16:** The VGG16 model outperformed DenseNet121, achieving an accuracy of 90.05% and a loss of 0.4956. The precision was 82.90%, recall was 75.84%, and the AUC was 0.9569. This model demonstrated a strong ability to accurately classify the severity of Alzheimer's disease **[Fig.3].**
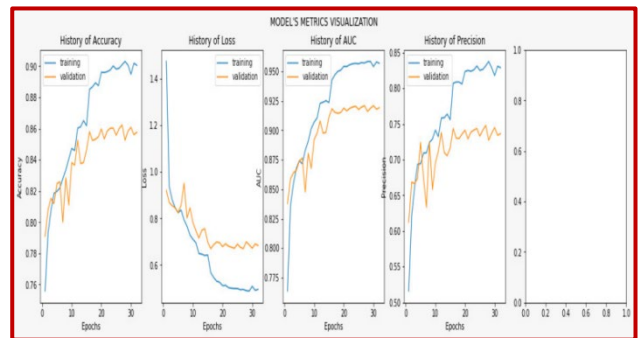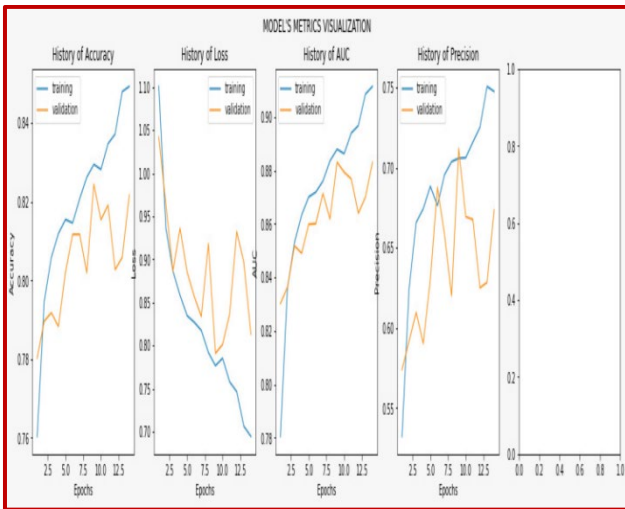

Fig 3: Model's Metrics Visualization for VGG16 Model

➢ **ResNet50:** The ResNet50 model achieved an accuracy of 84.02%, with a loss of 0.7226. The precision was 73.66%, recall was 56.19%, and the AUC was 0.9034. While the performance of ResNet50 was not as high as VGG16, it still demonstrated a good ability to distinguish between different classes of Alzheimer's severity **[Fig.4].**
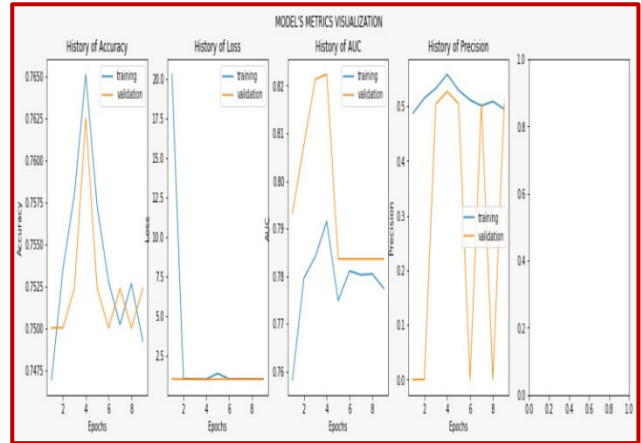
Fig 4: Model's Metrics Visualization for ResNet50 Model

➢ **MobileNetV2:** The MobileNetV2 model achieved an accuracy of 84.93%, with a loss of 0.6944. The precision was 74.76%, recall was 59.98%, and the AUC was 0.9115. This model showed a similar performance to ResNet50, demonstrating a good ability to classify the severity of Alzheimer's disease **[Fig.5].**
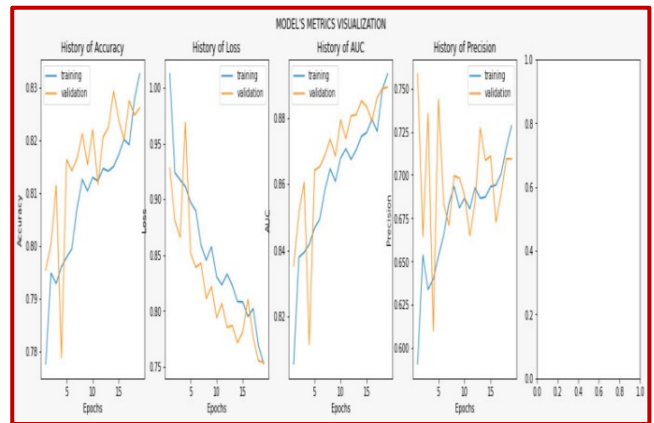

Fig 5: Model's Metrics Visualization for MobileNetV2 Model

➢ **AlexNet:** The AlexNet model achieved an accuracy of 74.92%, with a loss of 1.0389. The precision was 49.50%, recall was 15.47%, and the AUC was 0.7774. Despite its lower performance compared to other models, AlexNet could still distinguish between different classes of Alzheimer's severity to some extent **[Fig.6].**

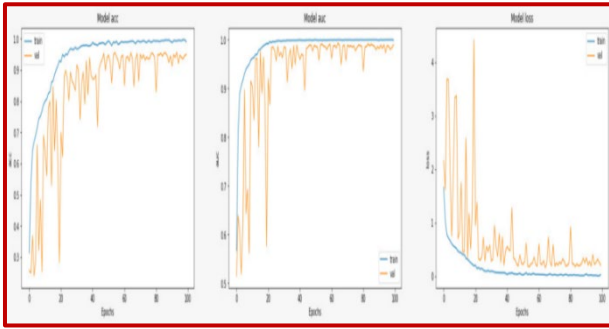**Fig 6:** Model's Metrics Visualization for AlexNet Model

➢ **Xception:** The Xception model achieved an accuracy of 83.26%, with a loss of 0.7528. The precision was 72.83%, recall was 52.71%, and the AUC was 0.8932. This model demonstrated a good ability to accurately classify the severity of Alzheimer's disease **[Fig.7].**

Fig 7: Model's Metrics Visualization for Xception Model

➢ **MobileNetV1:** The MobileNetV1 model outperformed all other models, achieving an accuracy of 99.21% and a loss of 0.0302. The AUC was 0.9991. This model demonstrated an exceptional ability to accurately classify the severity of Alzheimer's disease, making it the best model among those we tested **[Fig.8].**

Fig 8: Model's Metrics Visualization for MobileNetV1 Model

While all models demonstrated the ability to classify Alzheimer's disease severity to varying degrees, the MobileNetV1 model stood out as the most effective. Its high accuracy, low loss, and high AUC indicate its strong performance and potential for use in clinical settings. However, it's important to note that the choice of model should also consider factors such as computational resources and the specific requirements of the task.

5. Results and Discussion

In our study, we evaluated the performance of several DL models in classifying the severity of Alzheimer's disease based on MRI scans. The models we used included DenseNet121, VGG16, ResNet50, MobileNetV2, AlexNet, Xception, and MobileNetV1. Here, we discuss the results of our experiments and their implications. The DenseNet121 model achieved an accuracy of 77.77% and a loss of 0.9956. Despite its relatively lower performance compared to other models, DenseNet121 demonstrated a decent ability to distinguish between different classes of Alzheimer's severity. This suggests that DenseNet121 could be a viable option for Alzheimer's disease classification, particularly in scenarios where computational resources are limited. The VGG16 model outperformed DenseNet121, achieving an accuracy of 90.05% and a loss of 0.4956. This model demonstrated a strong ability to accurately classify the severity of Alzheimer's disease, suggesting that it could be a reliable

choice for this task. However, it's worth noting that VGG16 is a relatively complex model that may require substantial computational resources. The ResNet50 and MobileNetV2 models achieved accuracies of 84.02% and 84.93%, respectively. While their performances were not as high as VGG16, they still demonstrated a good ability to distinguish between different classes of Alzheimer's severity. These models could be suitable choices for Alzheimer's disease classification, particularly in scenarios where a balance between performance and computational efficiency is required. The AlexNet model achieved an accuracy of 74.92%, the lowest among the models we tested. However, it could still distinguish between different classes of Alzheimer's severity to some extent. This suggests that AlexNet could be a viable option for preliminary Alzheimer's disease classification, particularly in scenarios where computational resources are severely limited. The Xception model achieved an accuracy of 83.26%. This model demonstrated a good ability to accurately classify the severity of Alzheimer's disease, suggesting that it could be a reliable choice for this task. However, like VGG16, Xception is a relatively complex model that may require substantial computational resources. The MobileNetV1 model outperformed all other models, achieving an accuracy of 99.21% and a loss of 0.0302. This model demonstrated an exceptional ability to accurately classify the severity of Alzheimer's disease, making it the best model among those we tested. Its high performance suggests that it could be a highly reliable choice for Alzheimer's disease classification, particularly in scenarios where high accuracy is required. To summarize, each model we tested exhibited varying degrees of proficiency in classifying the severity of Alzheimer's disease, with the MobileNetV1 model emerging as the most proficient. However, the selection of a model should not solely be based on its performance. Factors such as available computational resources and the specific demands of the task at hand should also be taken into account. Looking ahead, we suggest that future investigations could delve into the application of ensemble methods, which amalgamate the predictions of multiple models, as a potential avenue for enhancing the precision of AD classification **[Fig.9]**.
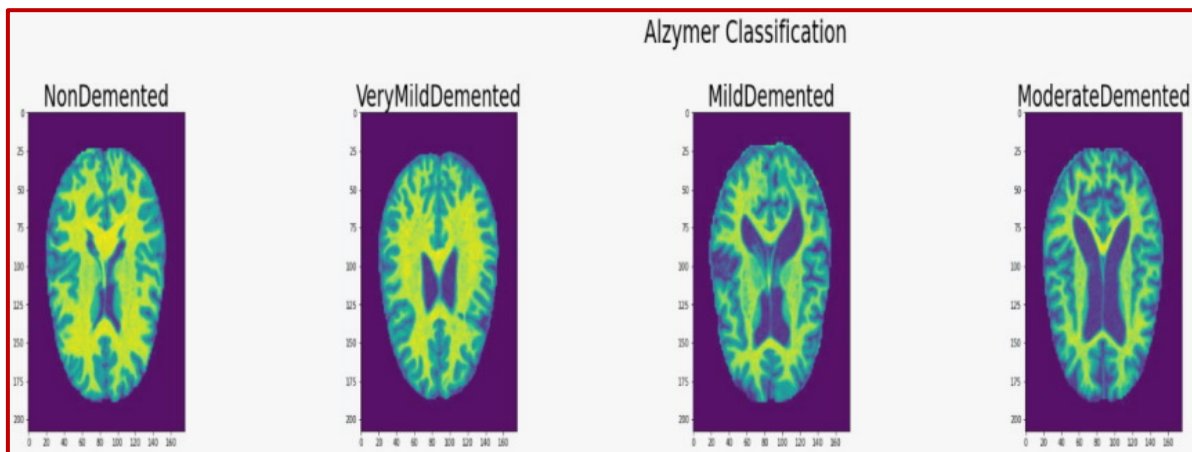
Fig 9: Classification of Alzheimer

6. Conclusion and Future Work

Our research aimed to explore the application of various DL models for the classification of AD severity using MRI scans. The models we evaluated included DenseNet121, VGG16, ResNet50, MobileNetV2, AlexNet, Xception, and MobileNetV1. Each model demonstrated varying degrees of proficiency in classifying the severity of Alzheimer's disease, with the MobileNetV1 model emerging as the most proficient. The MobileNetV1 model outperformed all other models, achieving an accuracy of 99.21% and a loss of 0.0302. Its exceptional performance suggests that it could be a highly reliable choice for AD classification, particularly in scenarios where high accuracy is required. However, the choice of model should not solely be based on its performance. Factors such as available computational resources and the specific demands of the task at hand should also be taken into account. While our research provides valuable insights into the application of deep learning models for Alzheimer's disease classification, there is still room for improvement and exploration. Future work could delve into the application of ensemble methods, which amalgamate the predictions of multiple models, as a potential avenue for enhancing the precision of Alzheimer's disease classification. Additionally, the exploration of other preprocessing techniques, such as different image normalization and augmentation methods, could potentially improve the performance of the models. Furthermore, the use of larger and more diverse datasets could help improve the generalizability of the models. In conclusion, our research underscores the potential of deep learning models in revolutionizing the diagnosis and prognosis of Alzheimer's disease.

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