AlzheimerNet-V3: Automated Deep Learning Approach for Detecting Alzheimer's Disease

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Introduction/Importance of Study:

Alzheimer's Disease (AD) stands as the highly prevalent form of dementia, culminating in a progressive neurological brain disorder characterized by deteriorating memory function and impaired daily activities due to brain cell damage. This singular ailment is both unique and fatal, underscoring the critical importance of early detection worldwide. Timely identification holds promise in preemptively addressing the future challenges faced by numerous individuals.

Novelty statement:

By scrutinizing the disease's ramifications via MRI imagery, Artificial Intelligence (AI) technology emerges as a valuable ally in categorizing AD patients, thus aiding in prognosticating the onset of this debilitating illness. In recent years, AI from Machine Learning (ML) tactics have proven instrumental in the diagnostic landscape of AD. This study employs a transfer learning methodology to accurately identify Alzheimer's patients using MRI examination. Specifically, we introduce an adapted deep learning model dubbed AlzheimerNet-V3, leveraging a tailored version of the Inception v3 architecture.

Material and Method:

Our investigation encompasses comprehensive experimentation and assesses the efficiency of AlzheimerNet-V3 in collaboration with further pre-trained specimens. Notably, AlzheimerNet-V3 achieves the conclusion of accuracy, the outcome of precision, recall, and development of F1-score was computed as 94.06% for all traits. Furthermore, comparative analysis against contemporary techniques underscores the efficacy of AlzheimerNet-V3 for Alzheimer's detection, highlighting its reliability for real-time implementation.

Keywords: Early Detection, Dementia, Cognitive Decline, Diagnosis, Classification, AlzheimerNet-V3.

Introduction:

Alzheimer's disease stands as particularly prevalent and debilitating psychological trouble in connection with the elderly population. It represents a progressive neurodegenerative condition leading to dementia, impacting various cognitive functions. This disease primarily affects the brain's neurons, triggering memory loss and a decline in cognitive abilities. In Alzheimer's patients, notable changes occur in brain structures, including an increase in ventricle size alongside reductions in cerebral cortex and hippocampus proportion. Figure 1 clarifies a stark contrast between optimal brain health and one afflicted by the pick's disease dementia. Recent reports indicate a staggering prevalence of dementia, affecting at least 55.2 million individuals worldwide. The financial burden associated with treating dementia patients has indeed escalated dramatically to an estimated $1.3 trillion, with projections suggesting this figure may exceed $2.8 trillion by the decade's end. While Alzheimer's disease remains incurable, its symptoms manifest gradually, emphasizing with crucial role of early detection in mitigating severe outcomes. To address this pressing need, there is a growing demand for computerized systems capable of detecting Alzheimer's disease, transcending traditional symptom-based approaches. Neuroimaging emerges as a pivotal domain, furnishing crucial insights into brain health through various imaging modalities such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Positron Emission Tomography (PET), and Diffusion tensor Imaging (DTI) [1]. Leveraging advanced computational capabilities, including natural language processing and image analysis, holds promise in accurately identifying Alzheimer's disease from diverse brain imaging data.

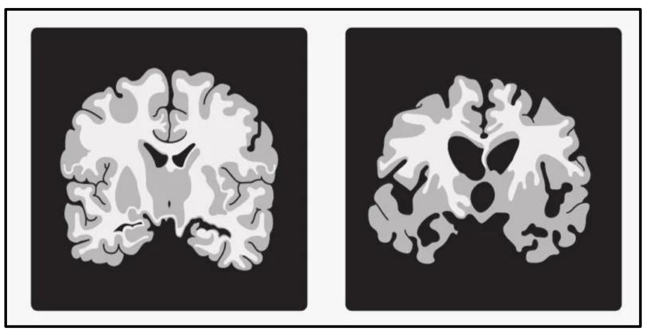

Figure 1: Normal Brain vs Alzheimer's Brain.

In recent years, the utilization of various ML and deep structure learning/ DL approaches has become even more popular in the context of discussing diagnostic evaluation. While ML models have demonstrated considerable success in identifying several diseases, DL outperforms for its efficiency and reduced time consumption, functioning akin to the intricate neural networks of the human brain. Within the domain of DL, transfer learning emerges as a prominent approach, leveraging pre-trained models to facilitate disease detection [2]. Transfer learning offers several advantages, including expedited training, enhanced classification accuracy, and reduced data requirements, making it a favored methodology among researchers for modern disease detection endeavors.

Among the cutting-edge techniques in neuroimaging, MRI stands as a cornerstone for obtaining high-resolution images of responsive components and tissue, such as the Brain, Lungs, Heart, and Bones [3]. Widely adopted in hospital and psychiatric settings, MRI provides unparalleled clarity and detail in brain scans, rendering it indispensable in diagnostic procedures. Notably, MRI datasets have served as invaluable resources for researchers in their quest to detect diseases like Alzheimer's. In the scope of our investigation, we capitalize on the function of the Pre-Trained NASA-Net-Mobile pattern in conjunction with an MRI dataset to execute binary classification for Alzheimer's disease. Our method is founded on the principles of transfer learning, harnessing the wealth of information embedded within MRI scans to bolster disease detection and diagnosis endeavors. Through the amalgamation of advanced DL methodologies and cutting-edge neuroimaging techniques, our approach strives to augment the authenticity and efficacy of Alzheimer's disease class distribution, potentially catalyzing advancements in patient care and management strategies.

Numerous Researchers have analyzed the data from a multidimensional perspective but patterns for recognizing the sequence used the ML approach in favor of Alzheimer's disease detection, contributing to the growing body of knowledge in this domain. M Bari et al [4] conducted a comparative analysis of diverse ML appraisal for Alzheimer's disease identification, leveraging the Open Access Series of Imaging Studies (OASIS) set of data. Their consideration encompassed the practice of multiple ML patterns, including linear regression, Support Vector Machine (SVM), Decision Tree (DT), and Random Forest (RF), with SVM emerging as the most promising model based on superior evaluation metrics. Similarly, Shahbaz et al. [5] embarked on a comprehensive examination of ML and data retrieval techniques using the Alzheimer's Disease Neurogenerative Initiative (ADNI) set of data. Their experimental findings showcased the generalized linear model's superior performance, boasting the maximum evaluation effectiveness of 88.24% among the tested algorithms. In a distinct approach, Alam et al. [6] devised an ML-supported methodology employing twin-SVM, Straight feature analysis, and wavelet transform for AD patient identification. Utilizing the ADNI dataset, they generated a confusion matrix to compute various evaluation metrics, highlighting the efficiency of their approach in disease classification. Furthermore, Saruar Alam et al. [6] proposed an enhanced DT sorter tailored specifically towards Alzheimer's detection. Deploying this improved category on the OASIS dataset for dual category yielded promising results, further corroborating the possibility of the ML approach in Alzheimer's problem identification. DL has appeared as a pivotal mechanism in the domain of disease detection, contributing remarkable potential in various healthcare applications. Al-Shoukry et al. [7] conducted an extensive review encompassing multiple studies employing DL methodologies regarding Alzheimer's problem identification. Their analysis revealed the predominant utilization of neuroimaging datasets among researchers, with a notable emphasis on the Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) approach regarding Alzheimer's identification purposes.

In a pioneering endeavor, Tuan et al. [8] devised a DL infrastructure tailored specifically for Alzheimer's identification. Employing CNN for cleavage a fusion of SVM and XG Boost for classification, the authors achieved notable strides in disease detection accuracy. Similarly, Murugan et al. [9] introduced a novelty CNN framework dubbed DEMNET, designed to expedite early exposure to Alzheimer's problems. Leveraging this framework on the Kaggle record yielded major advancements, surpassing existing methodologies in disease detection efficacy. Expanding on this trajectory, Feng et al. [10] devised a comprehensive DL framework integrating MRI and PET image data for feature extraction. Their approach involved the development of a 3D-CNN framework for Alzheimer's recognition, further enhanced through the incorporation of the FSBI-LSTM approach. Evaluation of this considered structure on ADNI record showcased promising results and, the significance of their possibility as a powerful mechanism in disease identification and management.

Numerous studies have delved into the efficacy of artificial neural network methodologies for Alzheimer's problem identification, elucidating its potential as a pivotal approach in the field. Naz et al. [11] conducted an in-depth investigation leveraging several get-ready frameworks to differentiate between separate classes of Alzheimer's disease. Their methodology involved preprocessing the dataset and subsequently applying diverse pre-trained models to the extracted features from various CNN architectures. The classification task was then executed through an SVM sorter. Experimental findings underscored the superiority of the VGG-19-SVM model over other pre-trained counterparts, demonstrating its efficacy in disease classification. In a parallel endeavor, Ghazal et al. [12] present comprehensive work wherein Alex Net already prepared a framework that was employed on the ADNI set of data. Similarly, Khan et al. [13] devised an artificial neural network framework addressing the challenge of big data requirements for learning methods. Employing an entropy-based technique, they successfully reduced the volume of the conditioning dataset by almost 20%, subsequently applying an improved VGG pattern toward the ADNI dataset for Alzheimer's disease identification. Moreover, Savaş et al. [14] embarked on an extensive exploration of 29 already prepared frameworks for Alzheimer's disease identification, with Efficient Net models emerging as the top performers in terms of evaluation metrics. This collective body of research underscores the escalating concern surrounding Alzheimer's disease and the imperative for early detection to mitigate its profound impacts.

Objectives:

Our study also contributes to this burgeoning field, leveraging pre-trained models for the categorization of Alzheimer's sufferers and healthy man controls. Our efforts aim to augment existing methodologies and enhance the accuracy of disease classification, thereby advancing our understanding and management of Alzheimer's disease.

Key Contributions

- We developed a unique AlzheimerNet-V3 approach for the quick release of Alzheimer's disease.
- The suggested approach effectively distinguished between Alzheimer's and normal brains with heightened authenticity.
- A relative study with current methods demonstrated the efficient capability of our technique in identifying Alzheimer's patients, suggesting its potential applicability in diagnostic centers.

Materials and Method:

This research primarily aims to recognize Alzheimer's disease patients utilizing a publicly available dataset on Kaggle [15]. The proposed workflow encompasses three key phases: data preprocessing, feature extraction, and multi-classification utilizing the AlzheimerNet-V3 architecture, as depicted in Figure 2. In the initial phase, data preprocessing entails rescaling and converting grayscale images into RGB format. Subsequently, in the feature extraction point, we adopted the InceptionV3 operational pattern by incorporating basic pools and compact levels to facilitate discrimination between Alzheimer's disease portrait and normal brain portrait. Following this, the recommended AlzheimerNet-V3 model is trained using the benchmark data, with experimentation conducted on the designated described testing set. Finally, our suggested framework effectively identifies Alzheimer's disease sufferers and distinguishes them from individuals with normal brain function.

Data Preprocessing:

We conducted an early compilation of the MRI Data sourced from Kaggle [15] to ensure their clarity and enhance their applicability within the collection. The employed dataset comprises four classes: Mild Demented, Moderate Demented, Very Mild Demented images, and non-Demented images. As part of preprocessing, we rescaled the images, initially collected as grayscale images from MRI scans. Converting these grayscale images into RGB format serves to enrich the available information while simultaneously mitigating noise and eliminating extraneous components. Consequently, the transformation of MRI pictures into RGB scale yields enhanced clarity and provides a more comprehensive dataset compared to grayscale images.

Convolutional Neural Network:

Convolutional Neural Networks (CNNs) represent the forefront of supervised accession methodologies, widely employed for image analysis and various classification tasks. The inherent pattern recognition capabilities of CNNs facilitate improved analysis of image datasets. A common CNN structure is made up of three primary layer types: convolutional layers (Conv), pooling layers (Pool), and fully connected layers (FC), as depicted in Figure 3.

Additionally, Activation layers and activation functions serve as pivotal components within the CNN structure. Convolutional layers play a central role in CNNs, as they possess the ability to detect intricate patterns within images. These layers are equipped with diverse filters designed to identify patterns present in the image dataset. The output of convolutional layers, termed feature maps, encapsulates data about discerned corners and other edge designs. Subsequently, this map of features is fed into the activation sheet to reduce its capacity. Within the FC (fully connected) tier, distinct Neurons are given weights to facilitate factor input collineation. However, aggregation of every characteristic at the FC layer may lead to multicollinearity issues in the CNN architecture. This challenge is commonly addressed through the incorporation of dropout layers, which selectively deactivate input neurons, mitigating the risk of overfitting. Activation functions play a crucial role in CNNs, generating output based on the intensity of input signals at individual neurons. Each layer of the CNN incorporates activation mechanisms to generate significant results. Generally, the interplay of convolutional, pooling, and fully connected layers, along with dropout layers and activation functions, enables CNNs to effectively analyze complex image datasets and extract valuable insights.

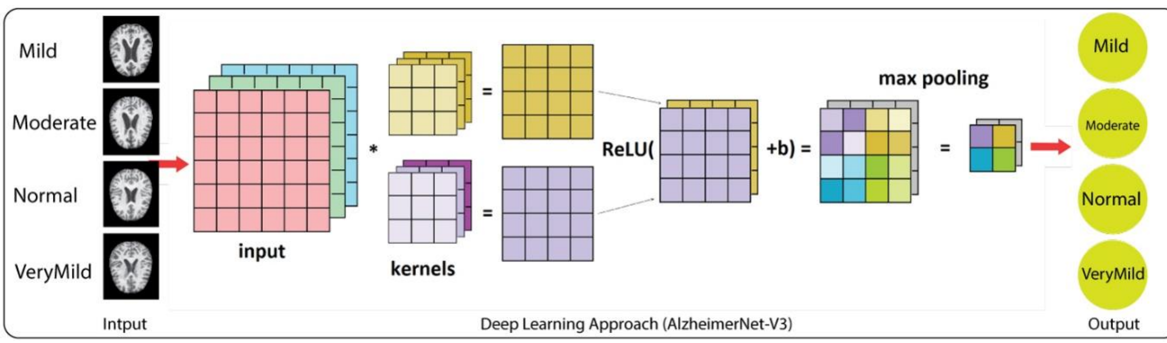

Figure 2: Workflow of the Proposed System.

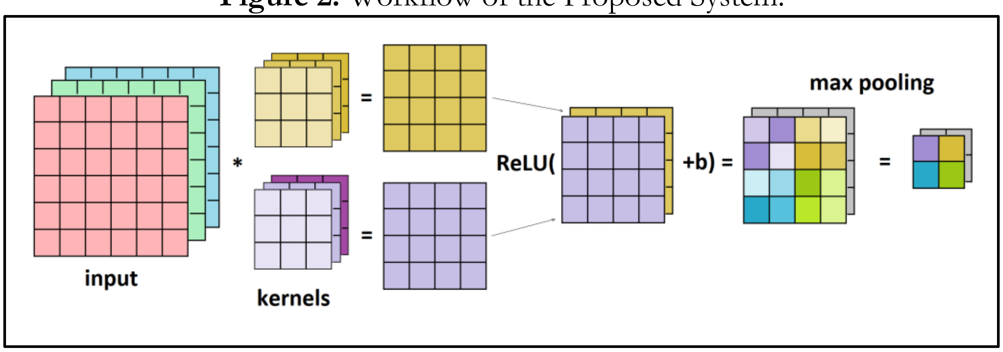

Figure 3: Generic Convolutional Neural Network.

Transfer Learning:

Transfer learning stands as a cornerstone method in the realm of developing deep learning or machine learning models, wherein information acquired from another objective is leveraged to enhance performance on another task. This approach necessitates similarity between the datasets employed in the initial and subsequent tasks. One of the foremost advantages of transfer learning lies in its ability to expedite the training process by obviating the need to commence differently. Through harnessing transfer learning, models have the potential to yield significant outcomes. Even when trained on limited datasets, thereby circumventing the resource-intensive task of collecting vast amounts of data [14]. Moreover, transfer learning contributes to reducing computational expenses, so models can be trained with less training data.

We utilized collected pictures in the recommended study to classify patients with Alzheimer's disease, necessitating the application of transfer learning on the Convolutional Neural Network (CNN) model previously taught using picture data. Previously trained prototype emerges as a prevalent approach for implementing computer vision in supervised learning. The aforementioned methodology empowers developers to capitalize on existing models pre-trained on expansive datasets, thereby expediting the development process for addressing contemporary challenges. Pre-trained models possess the capability to procure detail from large-scale classified and unclassified datasets, furnishing a robust foundation for predictive analysis in diverse problem domains.

The utilization of pre-trained models facilitates fine-tuning, wherein stored knowledge is refined to suit the nuances of specific problem contexts. This adaptability proves invaluable, particularly when confronted with limited datasets, as the pre-existing knowledge encapsulated within pre-trained models enhances prediction accuracy. Additionally, developers have the flexibility to utilize either the entire pre-trained model or select specific segments tailored to the requirements of the new task. In this work, we utilized the Inception V3 model's functional elements to multi-classify Alzheimer's patients exemplifying the versatility and efficacy of employing pre-trained models in addressing complex healthcare challenges.

AlzheimerNet-V3 Structure:

In this study, our primary focus is on the creation of a specialized computer vision framework, coined AlzheimerNet-V3, engineered particularly for self-regulating clinical detection. Our approach entails the customization of the Inception V3 pre-trained model, a widely acknowledged architecture renowned for its efficacy in image recognition tasks. By leveraging the functional layers of Inception V3 as a foundational backbone, we augment the model with an additional eighteen layers, strategically designed to enhance its discriminative capabilities. The architectural configuration of AlzheimerNet-V3 is meticulously crafted to accommodate complexities inherent in Alzheimer's disease detection. Illustrated in Table 1, the model exhibits a sequential structure, facilitating seamless connectivity between successive layers. Beginning with the utilization of the Inception V3 model, which comprises an extensive array of (5×5×2048) units, our framework efficiently processes input images, traversing through the intricate hierarchy of functional layers inherent in Inception V3. Following the initial processing phase, a pivotal global average pooling 2D layer is introduced helping to reduce the feature maps' spatial dimensions to 2048 units, thereby facilitating subsequent processing steps. Building upon this foundation, our framework contains a series of densely connected layers, denoted as dense_1, dense_2, dense_3, dense_4, and dense_5. These layers, featuring varying numbers of units (512, 256, 128, and 64 units, respectively), were strategically interlinked to optimize information flow and feature extraction capabilities.

Table 1: Details of the Proposed Method.

Layer (type)	Output Shape	Param #
inception_v3 (Functional)	(None, 4, 4, 2048)	21,802,784
Dropout	(None, 4, 4, 2048)	0
global_average_pooling2d	(None, 2048)	0
Flatten	(None, 2048)	0
batch_normalization_94	(None, 2048)	8,192
Dense	(None, 512)	1,049,088
batch_normalization_95	(None, 512)	2,048
dropout_1	(None, 512)	0
dense_1	(None, 256)	131,328
batch_normalization_96	(None, 256)	1,024
dropout_2	(None, 256)	0
dense_2	(None, 128)	32,896
batch_normalization_97	(None, 128)	512
dropout_3	(None, 128)	0
dense_3	(None, 64)	8,256

batch_normalization_98	(None, 64)	256
dropout_4	(None, 64)	0
batch_normalization_99	(None, 64)	256
dense_4	(None, 4)	260
Total params:		**23,036,900**
Trainable params:		**1,227,972**
Non-trainable params:		**21,808,928**

Concluding the architecture is the dense output layer, carefully engineered to accommodate the specific requirements of the dataset. With a focus on Alzheimer's disease classification, the dense output layer is configured to encapsulate four distinct classes, mirroring the class distribution within the dataset. In addition to architectural considerations, our framework also integrates advanced activation functions to facilitate non-linear transformations within the neural network. While traditional functions like tanh and sigmoid have historically been employed, Due to these functions' shortcomings, the usage of alternatives such as the rectified linear unit (ReLU) and its variations (ELU, leaky ReLU, and noisy ReLU). In our framework, we opt for the leaky ReLU activation function, chosen for its ability to mitigate the vanishing gradient problem and foster faster convergence during training.

Overall, AlzheimerNet-V3 represents a sophisticated amalgamation of cutting-edge architectural design, strategic layer configurations, and advanced activation functions, all tailored toward the specific task of Alzheimer's disease detection. Through meticulous design and rigorous experimentation, our framework intends to overcome current obstacles and open the door for an ever-more accurate and successful diagnosis of Alzheimer's. The activation function is determined by the equation provided below:

$$f(x) = \max(0.01 \times X, X) \quad (1)$$

The development of the Inception V3 model garnered attention because of its impressive results in picture categorization tests. Softmax, Avg pool, Convolutional, Pooling, Inception, and Dropout layers are among the 42 total layers of Inception V3, which was pre-trained on the ImageNet dataset with over a thousand classes. Application of various-sized parallel filters which allows for the capturing of various picture features, is fundamental to the first architecture. To mitigate the computational burden, these filters are factorized, therefore lowering the computational expense and parameter count. Auxiliary classifiers are incorporated to address issues related to gradient vanishing, enhancing the model's training stability. Moreover, reduction blocks are employed to downsize filter dimensions, achieved by adjusting the grid size of the feature map. This optimization strategy aids in preserving computational efficiency while maintaining the model's discriminative power. Enhanced efficacy and efficiency in picture classification tasks are among the benefits that the Inception V3 model provides. In our proposed architecture, we exclusively utilize the functional levels of Inception V3, such as the Inception, Pooling, Convolutional, and Reduction layers. By leveraging these layers, we aim to delineate Alzheimer's patient brains from those of healthy individuals with enhanced precision and efficiency.

Experimental Results and Discussion:

Dataset Description:

The Alzheimer's disease dataset that was used in this research is crucial for the development and evaluation of machine-learning models aimed at detecting and diagnosing Alzheimer's disease. Based on the degree of dementia, the individuals in the dataset are divided into four different classes: mildly demented, moderately demented, non-demented, and very mildly demented. Details are given in Table 2.

Training Set:

The training set consists of a diverse range of individuals, each categorized into one of the four dementia severity classes.

Mild Demented:

This category includes 717 individuals exhibiting mild symptoms of dementia. These individuals

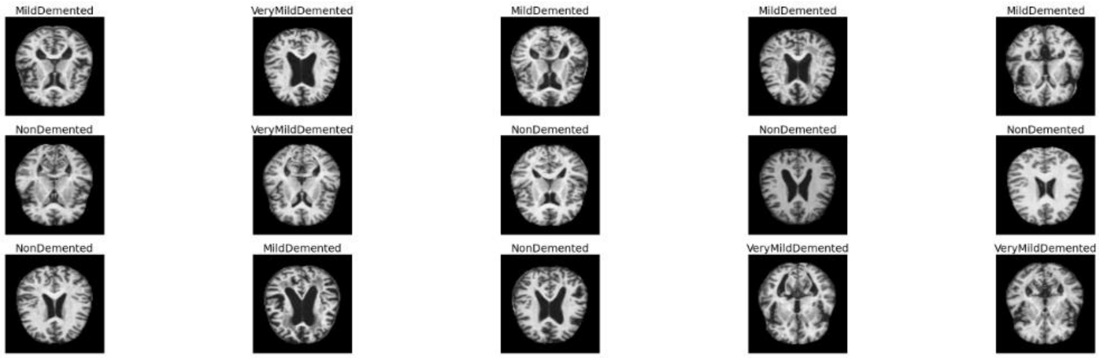

Figure 4: Image from Dataset [15].exhibited modest memory loss and cognitive decline, which are common indicators of subtle cognitive deficits.

Moderate Demented:

A smaller subset of individuals, comprising 52 cases, falls under this category. These individuals demonstrate more pronounced symptoms of dementia, with noticeable cognitive impairments affecting their daily functioning.

Non-Demented:

The largest category within the training set, consisting of 2560 individuals, encompasses those who do not exhibit symptoms of dementia. These individuals serve as the control group, providing a baseline for comparison with individuals in the dementia categories.

Very Mild Demented:

This category comprises 1792 individuals exhibiting early signs of dementia. Despite their relatively mild symptoms, individuals in this category may experience subtle memory lapses and cognitive deficits.

Test Set:

The test set follows a similar structure, encompassing individuals across the four dementia severity categories for the purpose of model evaluation.

Mild Demented:

The test set includes 179 individuals presenting with mild symptoms of dementia, mirroring the distribution observed in the training set.

Moderate Demented:

A smaller subset of individuals, totaling 12 cases, falls under this category in the test set.

Non-Demented:

Similar to the training set, the non-demented category in the test set comprises the largest subset, with 640 individuals serving as controls.

Very Mild Demented:

This category in the test set includes 448 individuals exhibiting early signs of dementia, providing a valuable cohort for evaluating model performance on early-stage dementia detection. The comprehensive nature of this dataset, encompassing individuals across various dementia severity levels, enables robust machine learning models' creation and assessment for the identification of Alzheimer's disease. The balanced distribution of individuals across the training and test sets ensures reliable model training and evaluation, ultimately contributing to advancements in Alzheimer's disease diagnosis and patient care.

Table 2: Details of Dataset.

Dementia Severity	Training Set	Test Set
Mild Demented	717	179
Moderate Demented	52	12

Non-Demented	2560	640
Very Mild Demented	1792	448

Results and Discussion:

We conducted a thorough evaluation process by dividing the dataset into separate training and testing subsets to gauge the efficacy of our suggested study. This division ensured a robust assessment of our model's performance across different data samples. The training set included eighty percent of the entire dataset, facilitating the model to learn patterns and features from a significant portion of the data. In contrast, the testing set, constituting 20% of the dataset, served as an independent validation cohort to evaluate the model's generalization ability. We utilized four key evaluation metrics including accuracy, precision, recall, and F1-score to measure the effectiveness of our suggested model, AlzheimerNet-V3. The capacity of the model to accurately categorize instances is just one of the many aspects of performance that these metrics shed light on to minimize false positives, and capture all relevant instances of a given class. Table 3 presents a detailed summary of performance metrics achieved by AlzheimerNet-V3. The model exhibited an impressive accuracy of 94.06 %, acknowledging its capability to correctly classify a vast majority of instances across all classes. Furthermore, the model demonstrated a high precision of 94.06%, highlighting its proficiency in minimizing false positives by accurately identifying true positive instances. The recall metric, which measures the model's ability to capture all relevant instances of a class, was also notable, with AlzheimerNet-V3 achieving a recall of 94.06%. Additionally, the F1-score, which represents the harmonic mean of precision and recall, further underscored the robustness of our model, reaching a value of 94.06%. In addition to evaluating our proposed model, we conducted comparative analyses with several other pre-trained models as well as ResNet-101, VGG-16, VGG-19, Mobile-Net-v2, and Mobile-Net-v3. These models were applied to the same Alzheimer's dataset to benchmark their performance against AlzheimerNet-V3 [15].

The results of our comparative analysis revealed notable performance variations across the different pre-trained models. While each model exhibited certain strengths, AlzheimerNet-V3 consistently outperformed its counterparts across all evaluated metrics. Notably, our model compared to VGG-16, VGG-19, Mobile-Net-v2, Mobile-Net-v3, and ResNet-101, attained superior accuracy, precision, recall, and F1-score. Overall, the superior performance of AlzheimerNet-V3 underscores its efficacy as a robust and reliable model for Alzheimer's disease. Our suggested approach shows great potential for improving patient outcomes and diagnostic accuracy in the management of Alzheimer's disease by exceeding current pre-trained models.

Table 3: Overall Functioning of the Suggested Model.

Model	Accuracy%	Precision%	Recall%	F1-Score%
VGG-16	93.42	90.12	89.78	88.51
VGG-19	91.22	88.89	88.42	90.42
Mobile-Net-v2	89.09	86.63	82.68	87.21
Mobile-Net-v3	88.42	84.32	83.41	85.19
ResNet-101	92.23	89.87	87.89	90.65
Proposed	94.06	94.06	94.06	94.06

Class	Precision	Recall	F1-Score	Support
0	0.96	0.99	0.97	480
1	1.00	1.00	1.00	480
2	0.93	0.86	0.89	480
3	0.88	0.91	0.90	480
Accuracy	-	-	0.94	1920
Macro Avg	0.94	0.94	0.94	1920
Weighted Avg	0.94	0.94	0.94	1920

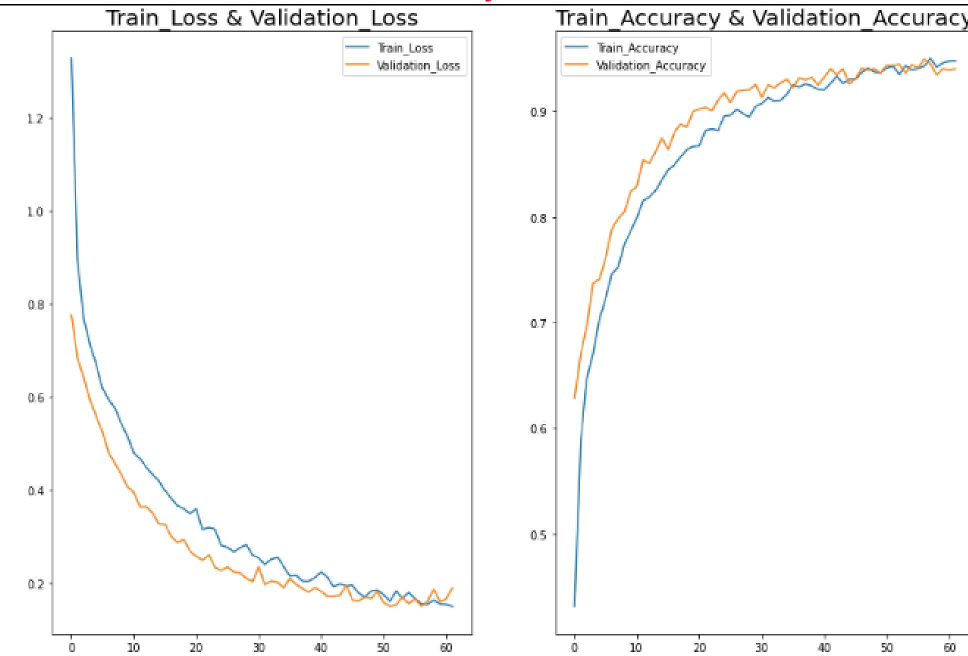

Figure 5: (a) Train Loss and Validation Loss, (b) Train Accuracy and Validation Accuracy.

Figure 5 (a) shows the train loss and validation loss while Figure 5 (b) shows the train accuracy and validation accuracy of the proposed AlzheimerNet-V3 approach. Next, we created a confusion matrix for multiple classes. Confusion matrices serve as valuable tools for quantitatively assessing the classification performance of a system on test data. They offer insights into various types of classification errors, enabling the calculation of multiple evaluation metrics. We used the confusion matrix in our study to calculate measures like recall, accuracy, precision, and F1-score. Table 4 presents the confusion matrix produced by our suggested system's testing data, which aims to differentiate between people with Alzheimer's disease and healthy people using the AlzheimerNet-V3 architecture. These results underscore the efficacy of the AlzheimerNet-V3 architecture in efficiently detecting Alzheimer's patients, indicating its potential utility in healthcare settings for Alzheimer's detection.

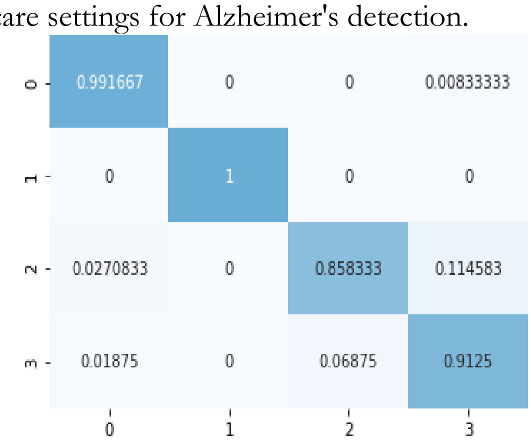

Figure 6: Normalized Confusion Matrix.

Here are the details shown in the table, the correct prediction, and the misclassification results.

Table 4: Confusion Matrix.

Predicted Class		Actual Class			
		476	0	0	4
	Non-Demented	0	480	0	0
	Moderate-Demented	13	0	412	55

	Non-Demented	9	0	33	438
	Very-Mild-Demented	Non-Demented	Moderate-Demented	Non-Demented	Very-Mild-Demented

Here are the details of the other metrics such as precision, recall, and F1-score in Table 5.

Table 5: Performance of AlzheimerNet-V3.

Class	Precision	Recall	F1-Score	Support
0	0.96	0.99	0.97	480
1	1.00	1.00	1.00	480
2	0.93	0.86	0.89	480
3	0.88	0.91	0.90	480
Accuracy	-	-	0.94	1920
Macro Avg	0.94	0.94	0.94	1920
Weighted Avg	0.94	0.94	0.94	1920

For Class 0, a precision of 0.96 suggested that when the model predicts a sample as belonging to Class 0, it is accurate approximately 96% of the time. The recall of 0.99 suggested that the model identifies about 99% of the actual Class 0 samples. The F1-score of 0.97, which is the harmonic mean of precision and recall, provided a balanced measure of the model's performance for Class 0. A similar interpretation applies to Class 1, with precision, recall, and F1-score all having 1.00, the model performs exceptionally well in identifying samples belonging to Class 1, achieving perfect scores for precision, recall, and F1-score. For these classes, the precision, recall, and F1 scores are slightly lower compared to Class 0 and 1, indicating that the model may have some difficulty in accurately identifying samples in these classes. However, the overall performance is still respectable, with F1 scores above 0.88 for both classes. However, the performance of a thorough comparative analysis between our proposed AlzheimerNet-V3 system and other contemporary methods is essential to gauge its effectiveness. Through this comparison, we aim to highlight the strengths and advantages of our approach to Alzheimer's detection. In the realm of Alzheimer's detection, CNNs have emerged as a popular choice among researchers. Table 6 provides an overview of alternative methods utilized by various authors for this purpose. For instance, Tian et al. [16] presented the MTFIL-NET model, which had an 86.00% accuracy rate in identifying Alzheimer's patients. LSTM+FS architecture, causing an accuracy of 88.00%. Using the EfficientNetB0 pre-trained CNN model, Savas et al. [14] were able to achieve a 92.98% accuracy rate. Moreover, Liu et al. [17] designed a deep separable CNN model, detecting Alzheimer's patients with 78.02% accuracy. Conversely, our AlzheimerNet-V3 model outperformed these findings, exhibiting a remarkable 94.06% accuracy, as illustrated in Table 6. This notable performance enhancement underscores the efficacy and potential of our proposed architecture, when it comes to identifying Alzheimer's illness. Furthermore, our approach offers several advantages, including robustness, scalability, and efficiency, making it a promising candidate for real-world applications in healthcare settings. Through this comprehensive comparative analysis, we aim to provide compelling evidence supporting the superiority of our AlzheimerNet-V3 system over other contemporary methods. We believe that our approach represents a significant advancement in Alzheimer's detection and holds promise for improving patient outcomes and healthcare practices [16].

Table 6: Comparing Performance Using Different Methods.

Authors	Method	Accuracy%
Tian et al. [16]	MTFIL-NET	86.00
S. Tabarestani et al. [18]	LSTM+FS	88.00
Savas et al. [14]	EfficientNetB0	92.98
Liu et al. [17]	Deep Separable CNN	78.02
Baseline [17]	Alex Net, Google Net	93.02 and 91.40
Proposed	AlzheimerNet-V3	94.06

Conclusion:

The proposed study addresses the pressing issue of Alzheimer's disease detection, a condition that represents a significant burden on global healthcare systems and individuals' quality of life. It impacts millions of people every year in the early stages of dementia. Early diagnosis is crucial for Alzheimer's sufferers, as symptoms may not worsen significantly if the disease is detected in its early stages. Considering the importance of this problem, creating an automated system to diagnose Alzheimer's is essential, especially in light of the rising number of older people who are suffering from dementia. In this study, we introduced a novel approach leveraging transfer learning, namely AlzheimerNet-V3, designed specifically for Alzheimer's disease detection. Built upon the Inception v3 pre-trained model, our proposed AlzheimerNet-V3 system aims to offer robust and efficient detection capabilities. In-depth, testing was also done to compare AlzheimerNet-V3's performance to other trained models that are frequently used to identify Alzheimer's disease. Our experimental results demonstrated that AlzheimerNet-V3 outperforms all other pre-trained models in terms of accuracy, precision, recall, and F1-score. Specifically, AlzheimerNet-V3 achieved an accuracy of 94.06%. These findings highlight how well our suggested method works to detect Alzheimer's patients with accuracy while reducing false positives. Additionally, we performed a comparison between AlzheimerNet-V3 and other cutting-edge methods to demonstrate the superiority of our methodology. The robust performance indicators achieved by AlzheimerNet-V3 indicate its potential utility in medical facilities and mental health clinics. By providing a dependable and effective method for Alzheimer's detection, AlzheimerNet-V3 shows promise in improving patient care and management strategies in the future.

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