ALZHEIMER'S DISEASE DETECTION USING MRI SCANS VIA RESNET 152 AND TRANSFER LEARNING

[1]A.V.D.N Murthy,[2]Tayya Neelima, [3]Pydi Divya, [4]Teela Chittibabu, [5]Veduruparthi VamsiPrakash
[1]Assistant Professor,[2]Student, [3]Student, [4]Student, [5]Student
[1]Department of Computer Science and Engineering,
[1]Lendi Institute of Engineering and Technology, Vizianagaram, India

Abstract - Alzheimer's disease (AD) is a progressive neurodegenerative disorder that primarily affects the brain, leading to a decline in cognitive function, memory loss, and behavior change. There is currently no cure for Alzheimer's disease. However, some treatments can help slow the progression of the disease and treat symptoms. So, Early and accurate detection of AD is crucial for timely intervention and potential treatment. Attributed to the shortage of medical staff, automatic diagnosis of Alzheimer's disease has become more important to relieve the workload of medical staff and increase the accuracy of medical diagnoses. Thus, for this purpose, an innovative approach to Alzheimer's disease detection leveraging machine learning, using MRI scans as inputs, and cutting-edge deep learning techniques, including ResNet 152 and Transfer Learning. This proposed work signifies a significant advancement in the field of AD detection, offering a non-invasive, cost-effective, and scalable approach that can potentially revolutionize early diagnosis and intervention. The integration of advanced machine learning and imaging technologies paves the way for more accessible and effective Alzheimer's disease screening, ultimately improving the quality of life for affected individuals and their families.

Index Terms - Alzheimer's disease, ResNet 152, Transfer Learning, MRI scans, neurodegenerative disorder, deep learning, Machine Learning

I. INTRODUCTION

Imagine living in a world where you can't hold onto your memories, no matter how hard you try. Every day, simple things become hard, like remembering tasks or recognizing loved ones. This is the reality for millions of people with Alzheimer's disease, a sickness that makes you forget who you are. It messes with your memory, your thinking, and how you act.

Alzheimer's disease (AD) stands as a formidable and pervasive challenge within the realm of neurodegenerative disorders, posing a significant burden on individuals, families, and societies worldwide. Named after Dr. Alois Alzheimer, who first identified the condition in 1906, this progressive brain disorder is characterized by the gradual deterioration of cognitive function, memory loss, and behavioral changes. As our global population ages, the prevalence of Alzheimer's disease continues to rise, highlighting the urgent need for a deeper understanding of its underlying mechanisms, effective diagnostic tools, and innovative therapeutic interventions.

In this paper, we'll explore Alzheimer's disease. We'll talk about what causes it, what happens to your body and mind when you have it, and some ways people try to treat it. We'll also look at how it affects families and the people who take care of those with Alzheimer's. Alzheimer's disease sneaks into your life quietly, starting with small signs that something isn't right. To understand how Alzheimer's works, we need to look at what's happening inside the brain.[3] People with Alzheimer's have two main problems in their brains: stuff called beta-amyloid plaques builds up between nerve cells, and there are tangled proteins called tau inside the brain's nerve cells. These things mess up how brain cells talk to each other and eventually make them die. As Alzheimer's gets worse, these problems spread throughout the brain, making it harder to remember things, solve problems, and understand what's going on around you. People might also notice changes in their loved ones' personalities or that they don't want to do things they used to enjoy. It's important to pay attention to these signs because they could mean someone has Alzheimer's disease.

The signs of Alzheimer's can start slowly. It is a condition that affects memory, thinking, and behavior. People with Alzheimer's may repeat themselves, forget conversations or events, misplace items, and get lost in familiar places. As the disease progresses, they may forget the names of family members, have trouble finding words, and struggle with tasks like managing finances or cooking. Decision-making becomes difficult, and personality changes may occur, such as depression, mood swings. Basic activities like dressing and bathing can become challenging. These symptoms worsen over time, making everyday life increasingly difficult for those with Alzheimer's and their caregivers.

Scientists think it's caused by a mix of genetics, lifestyle, and environmental factors. Sometimes, specific genetic changes can lead to Alzheimer's, but this is rare. Risk factors for Alzheimer's include getting older, family history, head injuries, and lifestyle factors like smoking and lack of exercise. But staying mentally and socially active, eating well, and exercising regularly may help lower the risk.

There is a growing enthusiasm for employing machine learning in the identification of metabolic diseases such as Alzheimer's and Diabetes, which impact a substantial global population. The prevalence of these conditions is escalating significantly each year. In Alzheimer's disease (AD), neurodegenerative changes affect the brain. Administering treatment during the early stages of AD proves to be more effective and inflicts fewer minor damages compared to treatments performed at later stages.

Though there is currently no cure for Alzheimer's, making early and accurate detection crucial for effective intervention and management. Traditional methods often rely on like the [4] Mini-Mental State Examination (MMSE) and clinical assessments, which may not provide the precision required for timely intervention. In [12] recent years, advanced imaging techniques, 2D T1-weighted Magnetic Resonance (MR) brain images, have emerged as promising tools for detecting structural and functional changes in the brain associated with Alzheimer's disease and enable physicians to detect signs of Alzheimer's disease with greater accuracy.

This paper focuses on leveraging the power of deep learning and transfer learning techniques, specifically ResNet 152, for the detection of Alzheimer's disease using MRI scans. By harnessing the capabilities of artificial intelligence, we aim to enhance the accuracy and efficiency of early diagnosis, offering a potential breakthrough in the realm of neuroimaging-based AD detection.

MRI scans provide detailed anatomical information, allowing for the visualization of structural alterations in the brain associated with Alzheimer's pathology. However, the complexity and subtle nature of these changes often challenge traditional analytical methods. The application of deep learning, and in particular, transfer learning with a robust architecture like ResNet 152, offers a novel approach to extracting intricate patterns from MRI data, potentially leading to more reliable and sensitive detection of Alzheimer's disease at its early stages.

As we go through the intersection of advanced imaging technology and artificial intelligence, this research seeks to explore the feasibility and effectiveness of employing ResNet 152 in transfer learning for Alzheimer's disease detection. Through this innovative approach, we aim to bridge the gap between cutting-edge technology and the pressing need for accurate and timely Alzheimer's disease diagnosis.

II. LITERATURE SURVEY

In[19] the realm of Alzheimer's disease (AD), inflammatory biomarkers signify molecules or substances in the body that provide insights into the presence or severity of inflammation. Researchers investigating AD have focused on exploring various inflammatory biomarkers present in the plasma (the liquid component of blood) of individuals affected by the disease. The exploration stems from the belief that chronic inflammation may contribute to the progression and development of Alzheimer's disease. Consequently, scientists are scrutinizing different markers of inflammation in the blood as potential indicators or contributors to the onset or advancement of the disease.

This [20] study aimed to pioneer a deep learning approach, employing a graph convolutional and recurrent neural network (graph-CNN-RNN) on a series of brain structural MRI data. The objectives were threefold: 1) to establish a diagnosis-guided probabilistic risk for characterizing whole-brain morphology at each time point; 2) to quantify the longitudinal trajectory of whole-brain morphology over the course of AD; and 3) to predict AD conversion as a function of age before clinical diagnosis.

The [21] early and precise diagnosis of Alzheimer's disease (AD) assumes a pivotal role in preventive measures, treatment strategies, and the overall care of patients by enabling the monitoring of its progression. Several ongoing research initiatives focus on the utilization of brain imaging techniques, including MRI, to detect Alzheimer's disease. MRI can assess the size and quantity of cells in the brain and reveal parietal atrophy in cases of AD.

A [10][14] new method called GAN-CNN-TL is suggested, using a combination of generative adversarial network, convolutional neural network, and transfer learning. This method is designed to handle the OASIS-1, OASIS-2, and OASIS-3 datasets, which are different but related datasets. Transfer learning is employed to adjust the parameters of the model by borrowing insights from previously trained models.

In their [22] 2018 study, Lan Lin et al. introduced a novel classification method designed to automatically distinguish patients with Alzheimer's disease from healthy controls based on MRI data. Features were extracted from the pre-trained convolutional neural network (CNN) using Alex Net, incorporating principal component analysis (PCA) and sequential

feature selection (SFS) for feature selection. The classification accuracy was assessed using a support vector machine (SVM).

In this[18] approach for detecting Alzheimer's disease based on brain MRI images using a deep learning-based Convolutional Neural Network (CNN). The model presented in the study consists of 12 layers and is designed for binary classification of Alzheimer's disease. The main contribution of the research is the development of this 12-layer CNN model, which achieves an impressive accuracy of 97.75% in detecting Alzheimer's disease from Brain MRI data.

[23] Researchers focusing on anomaly detection for Alzheimer's Disease in Brain MRIs via Unsupervised Generative Adversarial Learning approached the AD detection challenge by framing it as an anomaly detection problem, considering the OASIS-3 dataset's majority class as normal. They proposed a deep convolutional generative adversarial network with an encoder for AD detection, achieving an accuracy of 74.4%.

III. EXISTING SYSTEM

In[18] Existing System for detecting Alzheimer's disease (AD) detection heavily relies on machine learning methodologies, particularly the Support Vector Machine (SVM) classifier, which utilizes blood biomarkers for diagnosis. Alzheimer's disease, a progressive neurodegenerative condition characterized by cognitive decline, memory impairment, and reduced daily functioning, underscores the critical importance of early detection for effective intervention and management. Consequently, the development of precise diagnostic tools has emerged as a significant imperative within the medical community.

The integration of SVM classifiers with blood biomarkers has demonstrated potential in assisting AD diagnosis. [3]Biomarkers serve as quantifiable indicators of biological processes or states, with proteins like amyloid-beta and tau notably accumulating abnormally in the brains of AD patients. Through the analysis of these biomarker levels in blood samples, SVM classifiers can identify discernible patterns suggestive of either the presence or absence of AD, thereby facilitating diagnostic processes.

The Significance of Blood Biomarkers

- Blood biomarkers are measurable biological substances that indicate the presence, severity, or progression of a particular disease. When it comes to Alzheimer's disease, researchers have identified several promising biomarkers that can serve as invaluable indicators of the disease's onset and progression.
- Amyloid-β (Aβ) proteins play a pivotal role in the formation of amyloid plaques, one of the hallmark characteristics of Alzheimer's disease. Detecting Aβ proteins in the blood can help identify individuals at risk or those already in the early stages of Alzheimer's.
- Tau proteins contribute to the development of neurofibrillary tangles, another key feature of Alzheimer's disease. Elevated levels of tau proteins in the blood can indicate increased disease severity.
- Inflammatory processes within the brain are prevalent in Alzheimer's disease. Measuring neuroinflammation markers in the blood can provide valuable insights into disease progression and potential therapeutic targets.

Limitations

One of the main limitations of the current system lies in its binary classification approach,[14] wherein samples are divided into just two categories: AD-positive or AD-negative. Alzheimer's disease progression is heterogeneous, encompassing various stages and subtypes. A binary classification model oversimplifies this complexity and may overlook nuances that could aid in more nuanced disease detection. [16] Depending upon the stage of the disease. This division is critical because the patients at different stages of AD are required to be treated differently, and the same medication cannot be used for all of them.

Depending solely on blood biomarkers may not capture all aspects of Alzheimer's pathology, which could lead to misclassifications or errors in identifying whether someone has the disease or not. Therefore, it's important to further refine and validate the SVM model to enhance its precision in detection of AD.

The success of machine learning models, like SVM classifiers, largely depends on the caliber and amount of training data available. When it comes to AD diagnosis using blood biomarkers, datasets may encounter obstacles such as limited sample sizes, inconsistencies in data collection methods, and potential biases. Furthermore, acquiring top-notch biomarker data from clinical groups can be quite demanding, which poses challenges to building and validating dependable SVM models.

Blood biomarkers present a wealth of information that can be examined and analyzed by the SVM algorithm. The integration of blood biomarkers and the Support Vector Machine algorithm represents a major stride forward in the quest to detect Alzheimer's disease accurately and efficiently. By harnessing the power of measurable biological indicators and cutting-edge machine learning, healthcare professionals can detect the disease at its earliest stages, enabling improved

patient outcomes. As research continues to unlock new insights, this innovative approach brings hope and optimism to individuals and families impacted by Alzheimer's disease.

IV. PROPOSED SYSTEM: RESIDUAL NETWORKS

In the work of improving the detection of Alzheimer's disease (AD), researchers have been exploring new ways to enhance accuracy and accessibility. A significant breakthrough comes in the form of a proposed system that diverges from the traditional binary classification method. Rather than simply classifying cases as either AD-positive or AD-negative, this innovative system categorizes them into four distinct classes those are mild, very mild, moderate, and non-demented. This shift in approach not only provides a more detailed insight into the progression of AD.

A significant feature of the proposed system is its capacity to attain superior accuracy rates when compared to current methods. By dividing AD cases into four distinct categories, spanning from mild to non-demented, the system offers a more detailed evaluation of disease severity. This finer level of detail empowers clinicians to customize interventions and treatment strategies more precisely to meet the specific needs of each patient, resulting in better outcomes and enhanced quality of life.

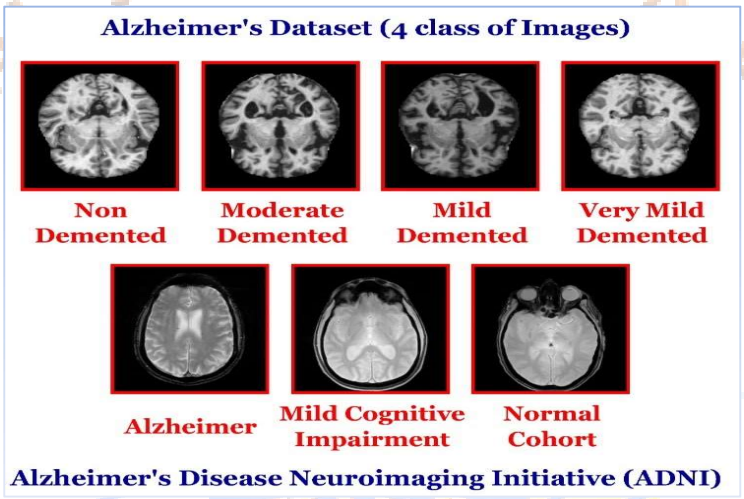


FIGURE 1:AD CLASSES

The Power of Brain Imaging

Magnetic Resonance Imaging (MRI) [12][10]is a powerful imaging technique that offers detailed insights into brain structure and function, making it invaluable in the diagnosis and monitoring of neurodegenerative disorders like Alzheimer's disease. The proposed system enhances its ability to accurately detect and characterize Alzheimer's disease. MRI provides clinicians with high-resolution images of the brain, allowing them to identify subtle structural changes associated with the disease, such as brain atrophy and the presence of abnormal protein deposits.[9] Atrophy in AD Progressive cerebral atrophy is a characteristic feature of neurodegeneration that can be visualized in life with MRI (best with T1-weighted volumetric sequences).

MRI offers a non-invasive and relatively accessible method for assessing brain health, making it suitable for use in routine clinical practice. Compared to other imaging modalities, such as Positron Emission Tomography (PET) scans, MRI is less expensive and does not involve the use of ionizing radiation, reducing potential risks to patients. The integration of MRI scans into the proposed system enhances its diagnostic accuracy and efficiency, enabling clinicians to identify and manage Alzheimer's disease more effectively.

V. METHODOLOGY

DATA ACQUISITION

The 10000 MRI images in the dataset show different parts of the brain and are divided into four groups: non-demented, mild, very mild, and moderate.[13][7] The Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset is the source of these photos. It is an extensive collection of MRI scans taken from people with Alzheimer's disease at various phases of the condition, from early cognitive impairment to advanced dementia. This dataset makes it easier to obtain a variety of MRI images that accurately depict the progressive nature of Alzheimer's disease.

DATA PREPROCESSING

Data Loading step involves getting the MRI scan images of the brain into the computer system where you'll be working. These MRI images contain a lot of detailed information about the brain's structure, which is essential for detecting Alzheimer's disease.

We further clean up the MRI scan data. This involves removing any irrelevant or corrupted information from the images. We want to ensure that only the essential features related to Alzheimer's disease detection remain in the data. In Noise removal MRI scans can sometimes have unwanted "noise" or artifacts that interfere with the accuracy of the images. In this step, we use techniques to filter out this noise, ensuring that the MRI images are as clear and accurate as possible. enables the extraction of specific anatomical features crucial for Alzheimer's disease diagnosis, such as the hippocampus or cortical regions affected by atrophy.

MRI scans may come in different sizes and resolutions. Rescaling involves standardizing the size and resolution of all MRI images so that they are uniform. This ensures consistency and makes it easier for the computer to process the images.

Normalization is a process where we adjust the intensity values of the MRI images to a standard scale. This helps in reducing variations in brightness and contrast between different images. It's important for ensuring that the computer model can accurately analyze the features of the MRI scans regardless of differences in lighting or imaging settings. Subsequently, the preprocessed MRI images are commonly resized or down sampled to a standardized resolution. This helps to streamline computational processes and optimize efficiency during analysis. Additionally, the dataset is partitioned into training, validation, and testing subsets to assess the performance of the ResNet model in Alzheimer's disease detection.

FEATURE EXTRACTION

MRI images of the brain are fed into the pre-trained model to extract features. As the model analyzes each MRI image, it progressively extracts hierarchical features at varying levels of abstraction. These features [1][2] encapsulate relevant details about brain structure and pathology linked to Alzheimer's disease (AD), including cortical thickness, hippocampal volume, and patterns of atrophy. Since employing ResNet-152, a deep learning model for classificaction tasks also handles automatic feature extraction, there is no necessity for using a distinct feature extraction method within our proposed approach.

The ResNet-152 architecture, pre-trained on the large-scale ImageNet dataset, serves as the backbone for feature extraction. [5][11]ImageNet is a vast dataset comprising millions of labeled images across thousands of categories and a large-scale ontology of images built upon the backbone of the WordNet structure. By pre-training ResNet-152 on ImageNet, the model learns to extract high-level features from images, such as edges, textures, and shapes. They encode valuable insights into the underlying brain anatomy and AD-related pathology, offering a detailed glimpse into the intricacies of the disease.

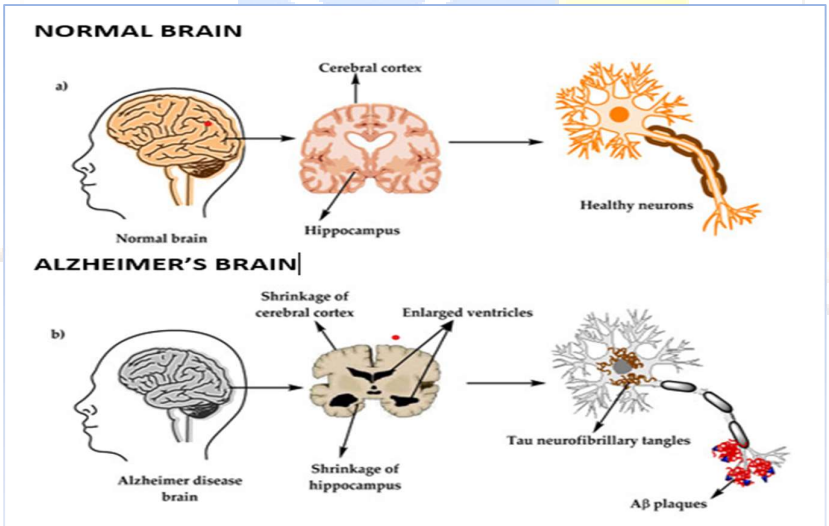


FIGURE 2: NORMAL BRAIN VS ALZHEIMER'S BRAIN

Transfer learning[6][8] involves refining the pre-trained ResNet-152 model using MRI images tailored for Alzheimer's disease detection. During this process, the features learned from the ImageNet dataset are repurposed and adjusted to suit the AD detection task. Typically, the final layers of the ResNet-152 model are retrained using the target dataset to tailor

the feature extraction process specifically for AD-related features. This customization ensures that the model effectively captures the variations of Alzheimer's disease pathology present in the MRI images.

How ResNet Works

In[15] recent years, the field of Image Processing and Recognition has witnessed significant advancements, particularly with the development of deep neural networks. As these networks become deeper and more intricate, there is a growing understanding that simply adding more layers can lead to diminishing returns in terms of accuracy. However, Residual Networks, or ResNets, have emerged as a solution to this challenge.

The tendency to add layers to neural networks lies in their ability to extract crucial features from complex images. For instance, initial layers may detect basic features like edges, while subsequent layers may recognize more intricate shapes. Yet, when networks exceed more layers, their performance can suffer, leading to decreased accuracy. This phenomenon is not attributable to overfitting but rather to the vanishing gradient problem, a common obstacle in deep learning.

The vanishing gradient problem arises when the gradients of the loss function concerning the weights of the initial layers diminish significantly. Consequently, these early layers receive minimal or no updated weight information during backpropagation, resulting in slow convergence or stagnation of the learning process. This issue is predominantly associated with the selection of activation functions and optimization techniques in deep neural networks.

When we backpropagate through a series of layers, we multiply gradients together. If these gradients are less than 1, which often happens in deep architectures, the resulting gradient can become very small as we move backward. In some cases, it may even vanish entirely, meaning that earlier layers aren't updated at all. This can lead to degraded performance, especially as we add more layers.

To address this issue, ResNet employs a deep residual learning framework that includes a unique feature called skip connections. These connections enable the model to learn identity functions, ensuring that higher layers perform at least as well as lower layers. By allowing layers to learn identity functions, even with additional layers added, their outputs remain equal to their inputs. This prevents the degradation of performance, as the additional layers don't negatively impact on the overall network performance.

Skip connections play a crucial role in addressing the vanishing gradient issue that can occur during the training of deep neural networks. These connections skip some layer in neural network and feed the output of one layer as the input to the next layers. This helps the network handle the flow of information more effectively. With skip connections, the network can also learn residual functions, which are like shortcuts that make it easier to train deeper models.

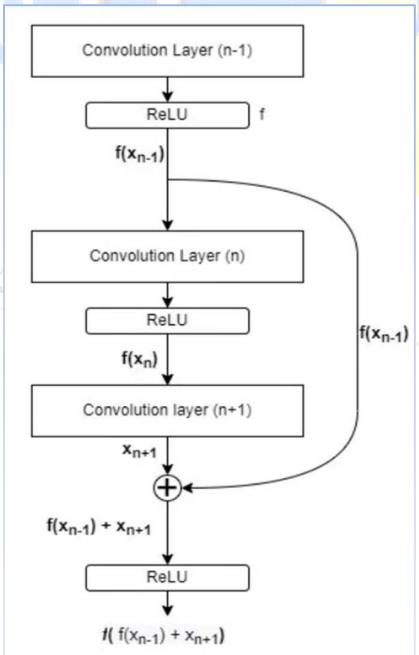


FIGURE 3:RESIDUAL BLOCK

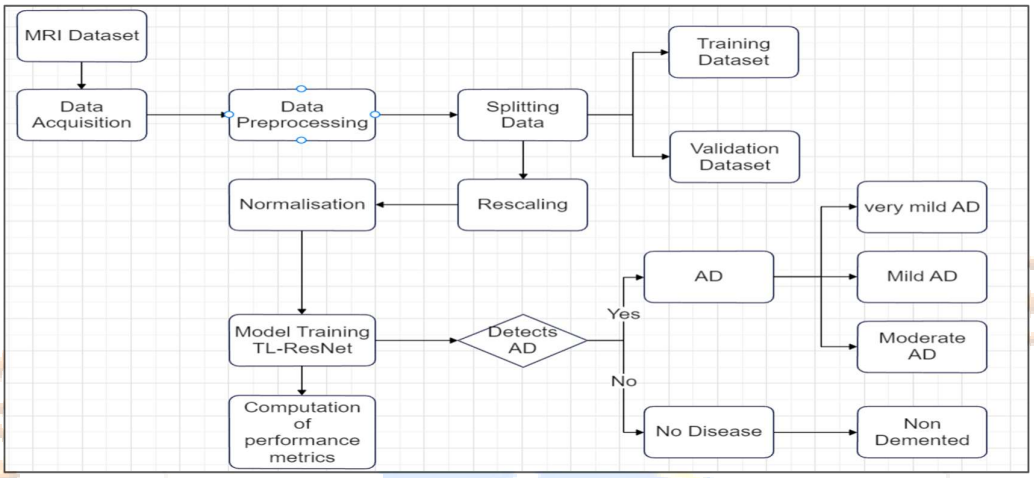
Advantages of ResNets:

ResNets have proven to be incredibly useful in many areas, including image recognition, object detection, and natural language processing. The skip connections in ResNets are especially helpful because they tackle the vanishing gradient

problem head-on, making training smoother and more efficient. Overall, ResNets have become a go-to choose for building deep learning models that deliver top-notch performance across various tasks.

ResNet152, a[18] model consisting of 152 layers, gained significant acclaim in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC), which assesses algorithms for recognizing objects and classifying images on a large scale. ImageNet 2015 test despite having fewer parameters than its popular counterpart, VGG19. This victory underscores the effectiveness of residual networks in tackling the challenges posed by deep architectures. At the core of a residual network are residual units or blocks, which incorporate skip connections, also known as identity connections, to facilitate Smoother information flow throughout the network.

VI. SYSTEM ARCHITECTURE



VII. EXPERIMENTAL RESULTS

We present all of the results of our experiments in the figures below.
Our experimental results demonstrate the efficency of our approach. By training our model on a comprehensive dataset of MRI scans, we achieved remarkable accuracy in distinguishing between Alzheimer's disease patients and healthy individuals. Compared to conventional manual diagnosis methods and existing automated approaches, our model exhibited superior performance, achieving training accuracy rate of 100%.

Moreover, our model's performance was further validated through rigorous testing on an independent dataset, where it consistently demonstrated high accuracy, achieving an accuracy rate of 95.86%.
Overall, our findings underscore the potential of MRI-based Alzheimer's disease detection using deep learning techniques. By combining the power of MRI scans with advanced neural network architectures, our approach offers a promising solution for accurate and efficient diagnosis, paving the way for improved patient care and management in clinical settings.

Graphical Representation of our Trained Model:

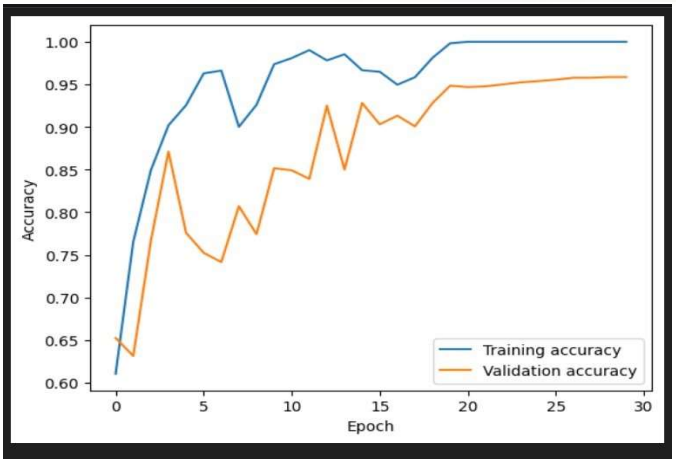


FIGURE 4:represents the Training accuracy and Validation accuracy with respect to epochs

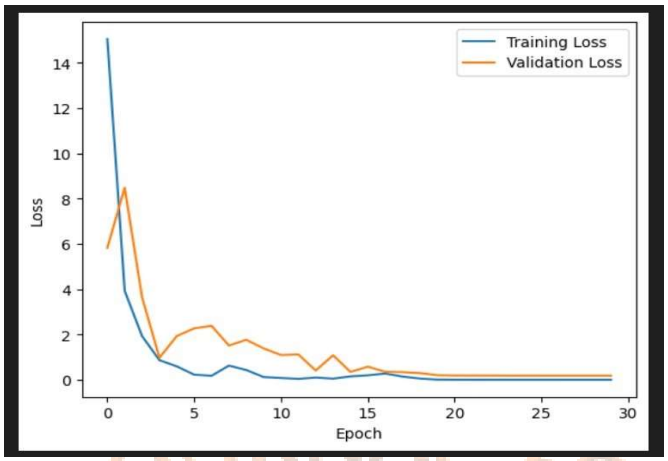


FIGURE 5: represents the Training loss and Validation loss with respect to epochs

Training accuracy curve (FIGURE 4) shows how well the model performs on the training dataset as training progresses. It demonstrates whether the model is learning from the training data and improving its performance over successive epochs or iterations. Validation accuracy curve shows how well the model generalizes to unseen data, as measured by a separate validation dataset. It indicates whether the model is overfitting or underfitting the training data.

Similarly, the training loss curve (FIGURE 5) shows how the loss function value changes over successive epochs or iterations during the training process. It indicates how well the model is fitting the training data. Lower training loss values suggest that the model is learning to minimize errors and accurately predict the training data. The validation loss curve shows how the loss function value changes over successive epochs or iterations on a separate validation dataset. It measures how well the model generalizes to unseen data. Higher validation loss values compared to training loss indicate that the model is overfitting to the training data and may not perform well on new, unseen data.

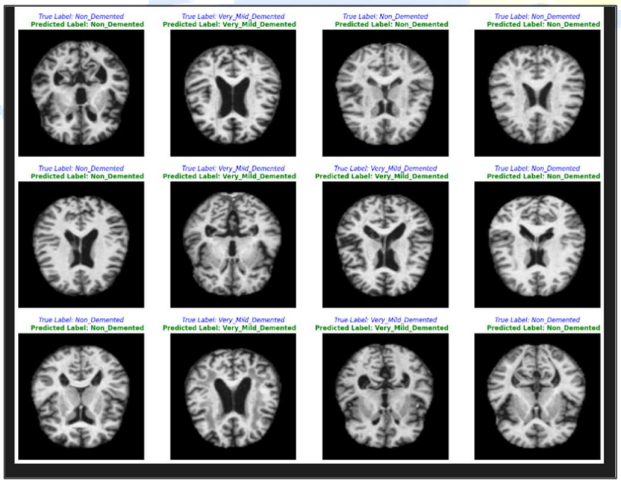


Figure 6: Depicts the model's performance was further validated through rigorous testing on an independent dataset

By testing the model on an independent dataset, we can validate whether the performance observed during training and validation stages holds true for new, unseen data. This independent evaluation provides confidence in the model's ability to generalize and perform well in real-world scenarios beyond the training data.

VIII. CONCLUSION

In conclusion, our research addresses the critical issue of time-consuming manual methods for Alzheimer's disease detection by proposing an innovative approach utilizing MRI scans. Through the implementation of ResNet-152 and ImageNet in a transfer learning framework, we have significantly reduced the time required for model development. Importantly, our approach has demonstrated superior accuracy compared to traditional methods. This breakthrough in efficiency and precision holds great promise for revolutionizing Alzheimer's disease diagnosis, emphasizing the potential impact of leveraging advanced technologies in the medical field for more timely and accurate results.

IX. REFERENCES

[1] Lerch J. P., et al., "MRI-based automated measurements of cortical thickness can effectively distinguish between Alzheimer's patients and healthy elderly individuals" Neuroimage (2008)

[2] ConvitA., et al., "Specific hippocampal volume reductions in individuals at risk for Alzheimer's disease" Neurobiology. Aging (1997)

[3] A. Delacourte, A. Defossez., "Alzheimer's disease: Tau proteins, the promoting factors of microtubule assembly, are major components of paired helical filaments" Journal of the Neurological Sciences(1986)

[4] M.F. Folstein et al., "Mini-mental state" A practical method for grading the cognitive state of patients for the clinician J Psychiatric Research (1975)

[5]Krizhevsky, A., Sutskever, I., & Hinton, G. (2012). ImageNet classification with deep convolutional neural networks.

[6]Ebrahimi-Ghahnavieh A., Luo S., Chiong R., "Transfer learning for Alzheimer's disease detection on MRI images," in IEEE (2019)

[7]Jack C. R., Jr., et al., "The Alzheimer's Disease Neuroimaging Initiative (ADNI): MRI methods," *J. Magn. Reson. Imaging(2008)*

[8]Raza, N., Naseer, A., Tamoor, M., Zafar, K., 2023. Alzheimer disease classification through transfer learning approach.

[9] Johnson, K.A., Fox, N.C., Sperling, R.A., Klunk, W.E., 2012. Brain imaging in alzheimer disease.

[10] Chui, K.T., Gupta, B.B., Alhalabi, W.S., Alzahrani, F.S., 2022. An mri scans-based alzheimer's disease detection via convolutional neural network and transfer learning.

[11] Deng, J., Dong, W., Socher, R., Li, L.J., Li, K., Fei-Fei, L., 2009. Imagenet: A large-scale hierarchical image database. 2009 IEEE Conference.

[12] EL-Geneedy, M., Moustafa, H.E.D.S., Khalifa, F., Khater, H., AbdElhalim, E., 2022. An mri-based deep learning approach for accurate detection of alzheimer's disease.

[13] ADNI, 2017b. Mri pre-processing. Available online: https://adni.loni.usc.edu/methods/mri-tool/mri-pre-processing/.

[14] C. Kavitha, V. Mani, S. Srividhya, O. I. Khalaf and C. A. T. Romero, "Early-stage alzheimer's disease prediction using machine learning models"(2022)

[15] "Residual networks (resnet) - deep learning", GeeksforGeeks, Jun 2020, [online] Available: https://www.geeksforgeeks.org/residual-networks-resnet-deep-learning/?ref=lbp.

[16] M. Shahbaz, S. Ali, A. Guergachi, A. Niazi and A. Umer, "Classification of alzheimer's disease using machine learning techniques"

[17] S. Tsang, "Review: ResNet — Winner of ILSVRC 2015 (Image Classification Localization Detection)", Medium, 2018

[18] E. Hussain, M. Hasan, S. Z. Hassan, T. Hassan Azmi, M. A. Rahman and M. Z. Parvez, "Deep Learning Based Binary Classification for Alzheimer's Disease Detection using Brain MRI Images", 2020

[19] "Inflammatory Markers in the Plasma of Alzheimer's Disease." A. R. Morgan et al., 2019 Jun;15(6):776-787

[20] Anqi Qiu, Liyuan Xu Chaoqiang Liu, "Predicting diagnosis 4 years prior to Alzheimer's disease incident Learnings from the Alzheimer's Disease Neuroimaging Initiative."

[21] "How MRI Serves in the Identification of Alzheimer's Disease."

[22] Lan Lin, Baiwen Zhang, Shuicai Wu, "A Hybrid CNN-SVM Approach for Alzheimer's Disease Classification using Structural MRI and the Alzheimer's Disease Neuroimaging Initiative (ADNI)" BEMES (2018)

[23] Jean Nathan Cabreza, Geoffrey A. Solano, Sun Arthur Ojeda, Vincent Munar, "Anomaly Detection for Alzheimer's Disease in Brain MRIs via Unsupervised Generative Adversarial Learning" IEEE (2022)