Early Alzheimer's Disease Stage Identification and Categorization Through Deep Learning

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***Abstract*—Alzheimer's disease diagnosis is an issue when the current protocols are ambiguous. The models employed in this work result in more transparency and decision making for patients and clinicians. The following deep learning models were used; CNN, AlexNet, DenseNet, and ResNet, with a comparison made between the models trained using the original dataset, and the same dataset converted to HSV format. For balancing the classes Synthetic Minority Oversampling Technique (SMOTE) was used during the preprocessing step. Accurate identification was highest for CNN on the original images and DenseNet on the images converted to HSV color space. The method does not only enhance the diagnosis precision but also enhances confidence since the doctors acquire an understandable explanation of the models' decision-making process, afford them a practical technique in enhancing Alzheimer's patients' care.**

***Index Terms*—Neural network architectures, Deep learn- ing algorithms, CNN, ResNet, DenseNet, AlexNet**

I. Introduction

Alzheimer's disease is a chronic and multifactorial brain disease that affects many patients around the globe. Not only that it brings enormous social and economic costs for patients and their families but also for the whole system of health care in nations. The disease manifests in short-term memory loss, attenuation of cognitive functions, and a decline in one's ability to complete daily tasks leading to the deterioration of the overall quality of life. It is especially important to diagnose the disease early and accurately, as this is the key to starting adequate treatment early, which can positively affect the quality of life of patients.

New development in deep learning has indicated a way forward in approaching these problems related to diagnosis of alzheimer's disease. Of these technologies, Convolutional Neural Networks (CNNs) have proved useful in MR image analysis. Stereotactic neuro MR imaging is another method of neurological functional status that would show structural changes that are characteristic of Alzheimer's disease. CNNs and other architectures of related types such as AlexNet, DenseNet and the architecture of Deep Learning models, such as ResNet, are capable of learning these complex features from these medical images making them ideal for use in analyzing and classifying brain images related to AD.

This work focuses on enhancing the accuracy and interpretability of Alzheimer's diagnosis by using deep learning models. Since this research improves the weighting of features and the model's decision making for clinicians and patients, it helps with interpreting the diagnostic process. To overcome the issue of class imbalance in the obtained dataset, Synthetic Minority Over-sampling Technique (SMOTE) algorithm was used during pre-processing stage. Furthermore, comparison of models trained from the original dataset and the new HSV format was made. The combination of these advanced approaches enhances the ability to obtain accurate and comprehensible results of Alzheimer's diagnosis, thereby helping the clinics to provide better and individualized treatment.

II. Literature Review

Ramzan et al. [1] Analyse the four-stage classification of AD using rs-fMRI and ResNet-18. Employing preprocessed data from the Alzheimer's Disease Neuroimaging Initiative (ADNI) cohort, they classify six progressive stages of AD: cognitively normal (CN), significant memory concern (SMC), early mild cognitive impairment (EMCI), mild cognitive impairment (MCI), late mild cognitive impairment (LMCI), and Alzheimer's disease (AD). As a result of this study, the utility of transfer learning using ImageNet pre-trained weights and ResNet-18 fine-tuning for clinical diagnostic support and early-stage indications can be affirmed with an average accuracy of 97.88%. Nawaz et al. [2] Suggest an actual-time method for the identification of the stage of Alzheimer's disease utilizing deep feature through the use of existing AlexNet model. Applying transfer learning on the OASIS dataset, their method obtains features from both the set of convolutional and fully connected layers of AlexNet and then classifying them with SVM, KNN, and RF. The proposed model reaches an accuracy of 99.21% using SVM, compared with handcrafted feature methods that used statistical and textural features with maximum RF accuracy of 84.93%. Their results highlight. The results demonstrated the effectiveness of deep learning and transfer learning for multiclass AD classification. Likewise, the multiclass classification CNN models that incorporated deep learning produced an accuracy of 92.85%, revealing the importance of utilizing transfer learning, alongside deep features in the early-stage identification of AD. Doaa et al. [3] examined the area of early Alzheimer's disease detection, classification. It highlights the in-depth deep learning methods with their application to the MRI and the PET imaging modalities. The system does a thorough job of assesing the different preprocessing techniques and faces challenges involved in both image and classification processing stages in particular. This work aims to review cutting-edge techniques and extract general implications about the intricacies of Alzheimer's disease diagnosis. Finally, from this probe, the survey looks to join in the progress of diagnostic tools and methodologies that are fighting Alzheimer's disease.

Hadeer A. Helaly et al. [4] This work presents the E2AD2C approach for early diagnosis and differentiation of Alzheimer's disease employing deep learning techniques. The framework applies two classification methods: Using CNN architectures, accurate identification of 2D and 3D brain scans was obtained at 93.61% and 95.17%, respectively, and a fine-tuned VGG19 model yielded an accuracy of up to 97% for multi-class classification of AD stages. The system includes the web-based application for the remote identification of the AD stage and advice, which is highly beneficial in the COVID-19 outbreak. Major accomplishments are data balancing through augmentation and obtaining high accuracy in binary and multi-class classifications. Jo et al. [5] The study investigates the use of deep learning with tau PET imaging for Alzheimer's disease (AD) classification. A 3D CNN model was developed to differentiate AD from cognitively normal individuals, achieving 90.8% accuracy using five- fold cross-validation. The layer-wise relevance propagation (LRP) technique highlighted significant regions, including the hippocampus and parahippocampal gyrus, as key contributors to classification. The framework was also applied to mild cognitive impairment (MCI) cases, yielding correlations of 0.43 for early MCI and 0.49 for late MCI with tau deposition. These results underscore the potential of deep learning for early AD detection. Venugopalan et al. [6] The study explores multi-modal deep learning frameworks to classify Alzheimer's disease (AD) stages using imaging, clinical, and genetic data. By employing 3D CNNs for MRI imaging, stacked autoencoders for clinical and genetic data, and integrating them, it achieved 78% external test accuracy for distinguishing between CN, MCI, and AD. Key biomarkers identified include hippocampus and amygdala for imaging, and memory-related scores for clinical data. The findings emphasize deep models' superiority over shallow models and highlight multi-modal integration's potential in improving AD staging.

Fathi et al. [7] This systematic review assesses deep learning approaches for early Alzheimer's disease (AD) detection via neuroimaging data. CNNs were highlighted as the most effective, particularly in ensemble setups. Transfer learning emerged as a key method for improving classification performance and reducing computational time. Binary classification between normal controls and AD achieved a mean accuracy of 93.99%, while early MCI (eMCI) detection yielded an average of 87.43%. The study calls for a benchmark platform to address comparability issues due to inconsistent datasets and preprocessing methods. Murugan et al. [8] The study proposes DEMNET, a CNN-based model for early detection of Alzheimer's Disease (AD) using MR images. By addressing dataset imbalance with SMOTE and evaluating four dementia stages, the model achieves 95.23% accuracy, 97% AUC, and a Cohen's Kappa of 0.93 using the Kaggle dataset. Comparisons with other models confirm superior performance, while testing on the ADNI dataset achieves 84.83% accuracy, demonstrating DEMNET's potential for robust AD diagnosis. Bringas et al. [9] The study introduces a CNN-based approach to classify Alzheimer's Disease (AD) stages using mobility data from smartphone accelerometers. The methodology includes data preprocessing to address class imbalance and a supervised learning model for stage prediction. Testing on a dataset of 35 AD patients showed 91% accuracy and an F1-score of 0.897, surpassing traditional classifiers like Random Forest and SVM. This approach emphasizes the feasibility of non-invasive monitoring using widely available devices to track AD progression effectively.

El-Sappagh et al. [10] This study presents a two- stage deep learning framework using LSTM models for Alzheimer's Disease (AD) detection and prediction of mild cognitive impairment (MCI) conversion time. Multimodal patient data, including neuroimaging and cognitive scores, were utilized. The classification stage achieved a 93.87% accuracy and 94.07% F1-score, while the regression stage predicted conversion time with a mean absolute error of 0.1375. The framework outperformed traditional ML models, demonstrating clinical potential for accurate AD progression prediction. A. Alorf et al. [11] The study addresses the critical challenge of classifying multiple stages of Alzheimer's disease (AD) using resting-state fMRI (rs- fMRI) data and deep learning. Unlike previous work limited to binary classifications, this research focuses on multi-label classification across six AD stages (CN, SMC, EMCI, MCI, LMCI, and AD). This research employs two deep learning models: Stacked Sparse Autoencoder (SSAE) and Brain Connectivity-based Graph Convolutional Network (BC- GCN). The models were evaluated using k-fold cross- validation, achieving accuracies of 77.13% (SSAE) and 84.03% (BC-GCN). Advantages include improved diagnostic performance and early detection potential, contributing to enhanced clinical decision support. However, challenges remain in generalizing these models to broader datasets and exploring individual variability in functional brain networks. R. R. Janghel et al. [12] The paper addresses the problem of accurate early diagnosis of Alzheimer's Disease (AD) using fMRI and PET images. The methodology involves preprocessing the ADNI dataset by converting 3D images to 2D and removing irrelevant boundaries, followed by feature extraction using a VGG-16 CNN model. The classification is performed using SVM, KNN, linear discrimination, and decision tree algorithms. Results show an impressive 99.95% accuracy for fMRI data and 73.46% for PET data, outperforming existing models. However, reducing execution time and improving PET accuracy remain open challenges for broader clinical applications.

M. EL-Geneedy et al. [13] The paper addresses the challenge of early Alzheimer's disease (AD) detection using MRI data and deep learning. The methodology involves preprocessing MRI images and applying convolutional neural network (CNN) architecture for classification across four AD stages: normal, very mild, mild, and moderate dementia. Achieving 99.68% accuracy, the model outperforms state-of-the-art methods, showcasing high sensitivity and specificity. Advantages include robust, early diagnosis, enhanced by transfer learning and data augmentation, overcoming data scarcity. However, open challenges remain in applying the framework to larger datasets and diverse populations to improve generalizability and detect AD progression more effectively. Mirzaei et al. [14] The paper focuses on machine learning techniques for diagnosing Alzheimer's Disease (AD), mild cognitive impairment, and other types of dementia. It explores methodologies like Support Vector Machines, Random Forests, and Convolutional Neural Networks (CNNs), emphasizing neuroimaging modalities such as MRI and PET. The advantages of CNNs include their ability to leverage transfer learning, reducing data requirements and improving early diagnostic accuracy. Results indicate up to 96% classification accuracy in some cases. However, challenges remain, including limited datasets and algorithmic variability. Future work should address standardization issues and explore emerging techniques like dynamic ensemble learning for enhanced predictive precision.

S. Sava et al. [15] The problem tackled by this paper is the critical need for early detection of Alzheimer's Disease (AD) stages using neuroimaging data. The methodology involves leveraging pre-trained Convolutional Neural Networks (CNNs) such as EfficientNet models to classify stages of AD based on MRI data from the ADNI database. EfficientNetB0 achieved the highest test accuracy of 92.98%, outperforming other models in sensitivity, precision, and specificity. This framework supports early diagnosis, facilitating timely intervention. However, challenges like limited data availability and variability in model performance remain open issues, prompting the need for standardized datasets and robust models for clinical applications.

Rajeswari et al. [16] sought and performed several transfer learning techniques to predict the Alzheimer's disease. They scheme like vgg-16, ResNet-50, and Xception as well with ADNI dataset of 6100 images. The dataset was divided into two categories: For each model, 80rest 2016 for 20 epoch. The presented model is VGG-19. the model that exhibited the superior performance was chosen. It was 98 then VGG-16 was 96with 61. Pushpa et al. [17] tried different state of the art algorithms of image enhancement to improve the quality and to remove noises such as median filtering and DnCNN. The dataset that is presented in this paper was parallelly acquire from Harvard and proceeded later implemented image segmented techniques based on gray matter and white matter. Techniques, such as threshold-based image segmentation, Region based segmentation and Adaptive thresholding, are later used. Next, a cnn model is employed with 2 hidden layers and 1 input layer as well as 1 output layer giving an accuracy of 0.88.

Srividya et al. [18], ResNet-50 deep learning algorithm as a primary tool was used. Identification of Alzheimer's disease was examined. They used ADNI2's sMRI data database for data. Proposed ResNet model was comprised of the five convolutional layers, which were ended with the classification layer that had both flatten and softmax operations. This model demonstrated 91% accuracy in the diagnosis of Alzheimer's disease. Besides, the next thing they did was they tested the model with saliency mapping as well. Kumar et al. [19] The paper examines deep learning methods for detecting Alzheimer's disease (AD), with a focus on convolutional neural networks (CNNs) and transfer learning with MRI data. CNN models like VGG16, DenseNet201, and ResNet50 are highlighted in a number of publications due to their effectiveness in classifying AD, frequently attaining high accuracy. Notable developments include the creation of AlzheimerNet, a CNN tailored for AD phases, and ADD-Net, a CNN made to deal with class imbalance. Techniques that use VGG architectures in conjunction with ensemble deep networks and support vector machines have also been emphasized for their potential to improve diagnostic accuracy and enable early diagnosis. By extracting intricate brain features from MRI scans, transfer learning is often used to leverage pre-trained models such as InceptionResNetV2 and ResNet50, which have shown promise in identifying different stages of AD. Nair et al. [20] This paper examines deep learning models for the detection of breast cancer, with an emphasis on hybrid and conventional CNN-based methods. Research shows that SVM and CNN work well together, achieving higher accuracy (93.35%) than stand-alone models like VGG16, ResNet-50, and InceptionV3.

Additionally, by overcoming SVM's limitations on larger datasets and preserving effective feature extraction and classification skills, CNN-SVM hybrids increase detection accuracy.

III. Data Description

The dataset available on Kaggle comprises two main folders, "train" and "test," where each is organized into four stages reflecting the severity of Alzheimer's disease. These stages— MildDemented, VeryMildDemented, NonDemented, and ModerateDemented—align with the RAWCOLD dementia protocols, representing varying depths of cognitive deficiency. Specifically, the dataset contains 717 images labeled as MildDemented, 1792 images as VeryMildDemented, 2560 images as NonDemented, and 52 images as ModerateDemented. To enhance the analysis, this dataset was converted into HSV (Hue, Saturation, Value) format to capture additional color-based features that may aid in distinguishing between stages. This HSV-converted dataset was then used alongside the original dataset in a comparative analysis, leveraging deep learning models such as CNN, DenseNet, and ResNet.

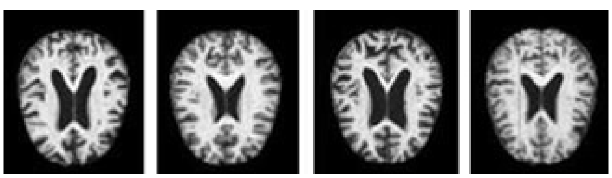

Fig. 1. Dataset

IV. Methodology

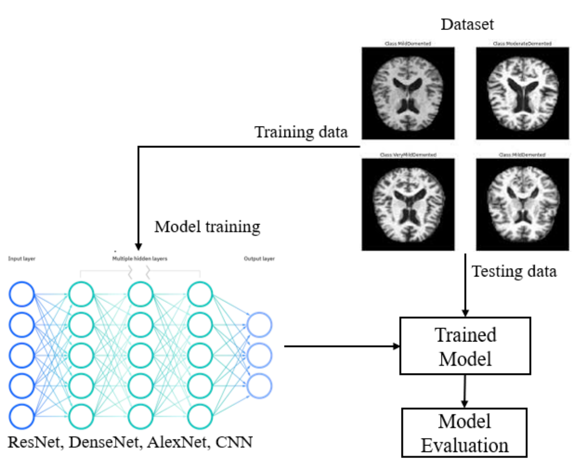

Fig. 2. Workflow of Deep Learning Model Development

A. Data Collection

The dataset comprising brain images organized into two main folders: "train" and "test." These images are further categorized into four classes representing different stages of Alzheimer's disease severity: MildDemented (717 images), VeryMildDemented (1792 images), NonDemented (2560 images), and ModerateDemented (52 images). This dataset was employed in its original form and was also converted into HSV format to capture additional color features for a comparative analysis of diagnostic accuracy.

B. Data Preprocessing

Normalization: To boost the quality as well as the generalization of our dataset, we made use of the ImageDataGenerator class in Keras to apply quite a number of data augmentation techniques. These methods that the algorithm used were rescaling pixel values to [0, 1] range, changing angle of image within 20 degrees range and applying zoom transformations within 0 – range. The transformation I will apply is shifting images 20% horizontally and vertically, and performing horizontal and vertical flips as well. These transformations were applied to provide an artificial wider and more diversified dataset, making the network less prone to overfit.

Synthetic Minority Oversampling Technique (SMOTE): SMOTE was used to create synthetic samples in order to oversample the minority classes in order to alleviate class imbalance, especially for the ModerateDemented category. By ensuring a more balanced dataset, this method enhances model performance on classes that are underrepresented.

C. Model Architecture

Four deep learning architectures were utilized to analyze the dataset: CNN, AlexNet, DenseNet, and ResNet. And trained both the datasets with these models. These architectures were chosen for their proven capabilities in image classification and feature extraction.

1) Convolutional Neural NEtwork (CNN): Realising this, for this study, a simple CNN was developed which included multiple convolutional layers, ReLU activation, max pooling and fully connected layers. CNNs are quite efficient in capturing spatial characteristics of medical images and are optimized for classification problems.

2) AlexNet: Three fully linked layers and five convolutional layers make up the eight layers of this ground-breaking deep learning model. AlexNet is effective for image classification problems because it uses ReLU activation for non-linearity and dropout to minimize overfitting.

3) DenseNet: This model links each layer with all the other layers to guarantee that the features were used to the maximum and gradients were passed through all the layers. This model aligns to scientific methodology and leads to few parameters but high accuracy, which makes it ideal for medical image analysis.

4) ResNet: This model incorporates residual learning with skip connections, to overcome the vanishing gradients issue in deep variants. This architecture allows for training of very deep networks while at the same time enjoying very high accuracy.

D. Model Evaluation

We have taken the four evaluation matrices (Accuracy, Precision, Recall, F1score) for model evaluation in our project.

V. Result and Analysis

The evaluation of four CNN-based models—AlexNet, DenseNet, ResNet, and a standard CNN—utilizes precision, recall, F1-score, and accuracy to measure performance.

The performance analysis of the deep learning models reveals significant insights into their effectiveness in diagnosing Alzheimer's disease. Among the models, CNN achieved the highest accuracy of 94%, demonstrating its strong capability in classifying the disease stages. DenseNet closely followed with an accuracy of 93%, indicating its superior ability to identify true positive cases with high reliability. AlexNet showed commendable performance with an accuracy of 87%, making it a robust choice for consistent predictions. ResNet50, while slightly lower in accuracy at 86%. Overall, CNN and DenseNet emerged as the most effective models, with DenseNet providing a balanced performance across all metrics and CNN excelling in accuracy. This highlights the potential of these models for reliable and precise Alzheimer's disease diagnosis as shown in table 1.

The performance analysis of the deep learning models reveals varying levels of effectiveness in diagnosing Alzheimer's disease. DenseNet and CNN demonstrated strong results, with DenseNet achieving an accuracy of 93%, highlighting its ability to identify true positive cases effectively. CNN followed closely with an accuracy of 91%, excelling in F1 score (98%) and precision (95%), making it particularly reliable for accurate predictions. AlexNet also showed competitive results with an accuracy of 87%, and high recall (93%) and precision (93%), making it a strong contender for consistent classification. ResNet50, however, underperformed relative to the other models, with lower accuracy (76%), recall (78%), F1 score (75%), and precision (76%), suggesting it may not be as effective for Alzheimer's disease detection in this context. Overall, CNN and DenseNet were the most reliable models, offering high diagnostic performance for Alzheimer's classification as shown in table 2.

In the model's classification, green regions highlight features supporting the prediction, while red areas suggest opposing evidence. For class 2 (healthy), green regions likely represent normal brain structures, with red areas indicating potential abnormalities or mixed features, suggesting the brain may not be entirely healthy. For class 3 (disease), green areas correspond to regions associated with disease, while red areas argue against it. The balance of green and red in each class helps the model make decisions, but significant red areas in class 2 indicate that the prediction might not be fully confident, and further clinical validation is needed.

VI. Conclusion

In conclusion, the deep learning models evaluated in this study—CNN, AlexNet, DenseNet, and ResNet— demonstrated promising performance in diagnosing Alzheimer's disease, with DenseNet and CNN standing out as the most effective models. DenseNet achieved the highest recall, F1 score, and precision, making it particularly strong in identifying true positives and minimizing false negatives. CNN, on the

DL Models	**Accuracy (%)**	**Recall (%)**	**F1 Score (%)**	**Precision (%)**
ResNet50	94.00	94.00	94.00	94.00
InceptionV3	87.00	87.00	87.00	87.00
DenseNet	92.00	92.00	92.00	92.00
CNN	89.00	89.00	89.00	89.00

TABLE I
Performance comparison for deep learning models

DL Models	**Accuracy (%)**	**Recall (%)**	**F1 Score (%)**	**Precision (%)**
ResNet50	76	78	75	76
InceptionV3	87	93	92	93
DenseNet	93	97	92.00	93
CNN	91	92	98	95

TABLE II
Performance comparison for deep learning models in HSV

Fig. 3. Accuracy graph of DenseNet 121

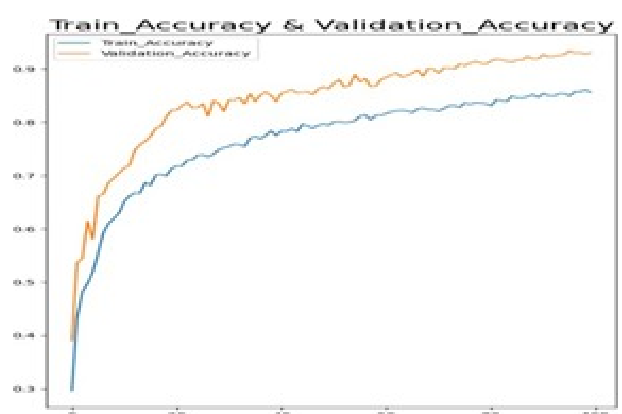

Fig. 4. Accuracy graph of ResNet 50

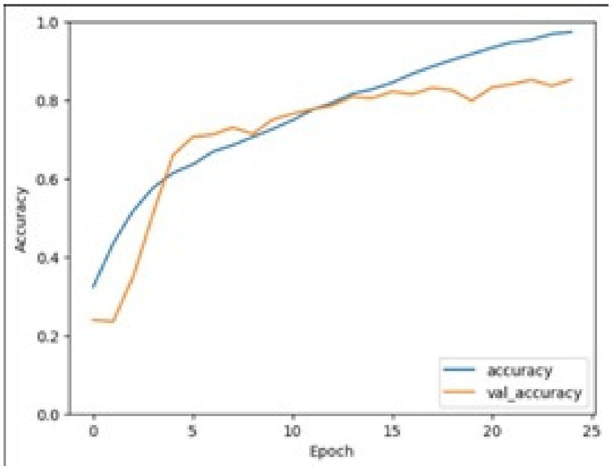

Fig. 5. Accuracy graph of AlexNet

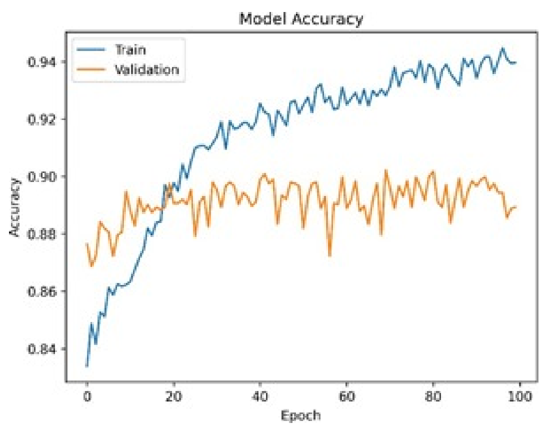

Fig. 6. Accuracy graph of CNN

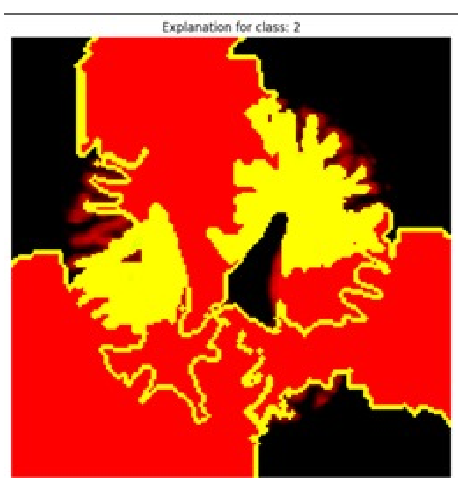

Fig. 7. RGB Analysis for DenseNet121

Fig. 8. RGB Analysis for ResNet-50

Fig. 9. RGB Analysis for AlexNet

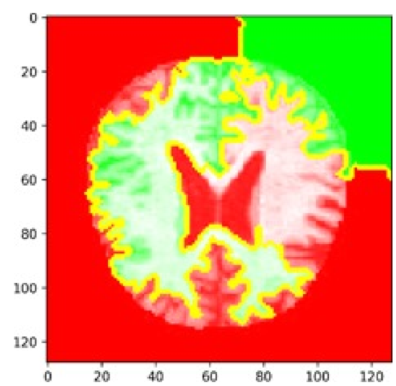

Fig. 10. RGB Analysis for CNN

Fig. 11. Accuracy graph of DenseNet 121

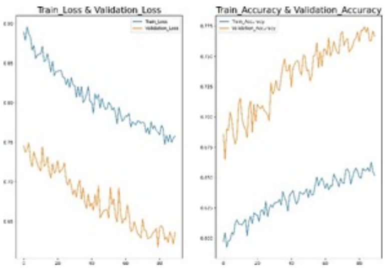

Fig. 12. Accuracy graph of ResNet 50

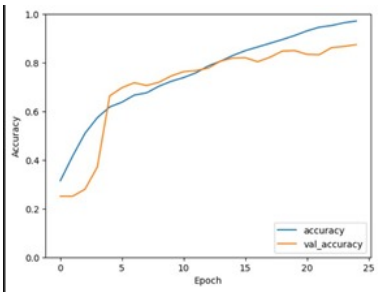

Fig. 13. Accuracy graph of AlexNet

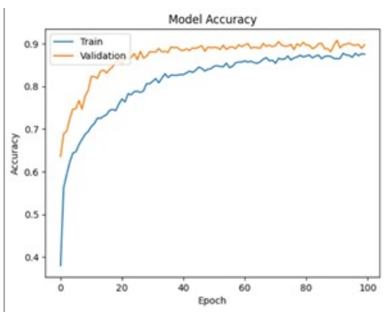

Fig. 14. Accuracy graph of CNN

Fig. 15. RGB Analysis for DenseNet121

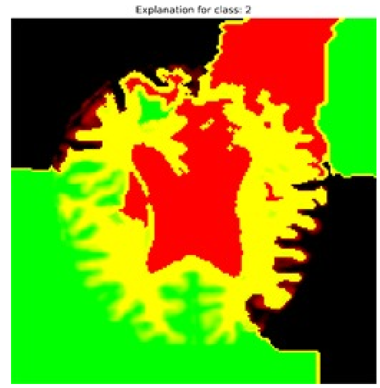

Fig. 16. RGB Analysis for ResNet-50

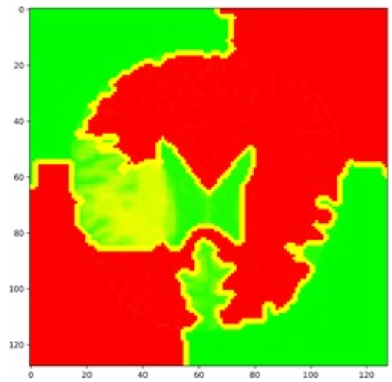

Fig. 17. RGB Analysis for AlexNet

other hand, exhibited the highest overall accuracy, showcasing its strong classification ability. While AlexNet and ResNet performed well, they were slightly less effective in comparison. These results emphasize the potential of deep learning techniques, especially CNN and DenseNet, in improving the accuracy and reliability of Alzheimer's disease diagnosis, supporting the use of these models in clinical settings for enhanced patient care.

REFERENCES

[1] Narmada, Nakka, Vishal Shekhar, and Tripty Singh. "Classification of Kidney Ailments using CNN in CT Images." 2022 13th International Conference on Computing Communication and Networking Technologies (ICCCNT). IEEE, 2022. (Amrita Paper)

[2] Ruhul Amin Hazarika,Ajith Abraham, Samarendra Nath Sur,Arnab Kumar Maji, Debdatta Kandar " Different techniques for Alzheimer's disease classification using brain images: a study " published on 2021 International Journal of Multimedia Information Retrieval.

[3] Doaa Ahmed Arafa, Hossam El-Din Moustafa, Amr M.T Ali-Eldin & Hesham A. Ali" Early detection of Alzheimer's disease based on the state-of-the-art deep learning approach: a comprehensive survey" published on 2022 Multimedia Tools and Applications.

[4] Modupe Odusami, Rytis Maskeliu¯nas1, Robertas Damasˇevicˇius2, Sanjay Misra" Explainable Deep-Learning-Based Diagnosis of Alzheimer's Disease Using Multimodal Input Fusion of PET and MRI Images" published on 2023 Journal of Medical and Biological Engineering.

[5] Hina Nawaz,Muazzam Maqsood, Sitara Afzal,Farhan Aadil,Irfan Mehmood & Seungmin Rho "A deep feature-based real-time system

for Alzheimer disease stage detection" published on 2021 Multimedia Tools and Applications.

[6] Rajeswari, S. S., & Nair, M. A transfer learning approach for pre- dicting alzheimer's disease. Paper presented at the 2021 International Conference on Nascent Technologies in Engineering, ICNET 2021 - Proceedings - Conference paper (Amrita Paper) 10.4230/OASIcs.SLATE.2016.5.

[7] B.R.Puspha,P.S.Amal,Nayana.P.Kamal "Detection and Stagewise Classification of Alzheimer Disease Using Deep Learning Methods" International Journal of Recent Technology and engineering(IJRTE) ISSN: 2277-3878, Volume-7, Issue-5S3, February 2019 - Journal paper (Amrita Paper)

[8] Hamza Ahmed Shad, Quazi Ashikur Rahman, Nashita Binte Asad, Atif Zawad,S.M.Faiaz Mursalin "Exploring Alzheimer's Disease Prediction with XAI in various Neural Network Models" IEEE Region 10 Conference (TENCON) -2021 - Conference paper.

[9] Srividya. L, Sowmya V, Vinayakumar R, Gopalakrishnan EA, and Soman KP." Deep learning-based approach for multi-stage diagnosis of Alzheimer's disease."Multimedia Tools and Applications(2023): 1-24. Multimedia Tools and Applications82, no. 14 (2023) - Journal (Amrita Paper) 03

[10] Soujanya R,Syamala Maganti, Sai Hanuman A "Deep Transfer Learning Models for Alzheimer's Disease Classification using MRI Images" international journal of Intelligent systems and applicationss in enginerring-2023 - Journal paper.

[11] Ishaan Batta, Anees Abrol, Vince Calhoun" A Multimodal Deep Learning Approach for Automated Detection and Characterization of Distinctly Salient Features of Alzheimers Disease" presented on 2023 IEEE 20th International Symposium on Biomedical Imagin.

[12] K. Muthamil Sudar, P. Nagaraj, S. Nithisaa, R. Aishwarya, M. Aakash, S.Ishwarya Lakshmi. " Alzheimer's Disease Analysis using Explainable Artificial Intelligence (XAI)". Paper presented on Proceedings of the International Conference on Sustainable Computing and Data Communication Systems (ICSCDS-2022) - Conference paper.

[13] Abhishek Raj,Sumit Bujare,Anil Gorthi,Jahan Malik,Abhradeep Das,Ashish Kumar. " Alzheimer's Disease Recognition using CNN Model with EfficientNetV2". Paper presented on 2022 2nd Asian Conference on Innovation in Technology - Conference paper.

[14] Gokce UYSAL, Mahmut OZTURK." Classifying Early and Late Mild Cognitive Impairment Stages of Alzheimer's Disease by Analyzing Different Brain Areas". Paper presented on 2020 Medical Technologies Congress.

[15] Janani Venugopalan, Li Tong, Hamid Reza Hassanzadeh & MayD. Wang" Multimodal deep learning models for early detection of Alzheimer's disease stage" Paper presented on 2021 Scientific Report.

[16] M. Khojaste-Sarakhsi , Seyedhamidreza Shahabi Haghighib,Elena Marchiori "Deep learning for Alzheimer's disease diagnosis" paper presented on 2022 Artificial Intelligence in Medicine.

[17] Alejandro Puente-Castroa,, Enrique Fernandez-Blanco , Alejandro Pazosa ,Cristian R. Munteanu "Automatic assessment of Alzheimer's disease diagnosis based on deep learning techniques" presented on 2020 Biomedical Research Institute of A Corun˜a.

[18] Esra C¸ ankaya Polat, Albert Gu¨veni "Detecting Alzheimer Disease on FDG PET Images Using a Similarity Index Based on Mutual Information1" published on 2020 Medical Technologies Congress.

[19] Kumar, K. Sanjeev, B. Saketh Reddy, and M. Ravichandran. "Alzheimer's Disease Detection Using Transfer Learning: Performance Analysis of InceptionResNetV2 and ResNet50 Models." 2023 Seventh International Conference on Image Information Processing (ICIIP). IEEE, 2023.(Amrita Paper)

[20] Nair, Nipun B., et al. "Deployment of breast cancer hybrid net using deep learning." 2022 13th International Conference on Computing Communication and Networking Technologies (ICCCNT). IEEE, 2022.(Amrita Paper)