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Early Detection of Alzheimer's using CNN based Deep Learning

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ABSTRACT: Alzheimer's disease (AD) is a neurodegenerative condition with progressive cognitive impairment, memory loss, and changes in behavior. Its early diagnosis is important to enable timely intervention and better patient outcomes. Nonetheless, the conventional diagnostic methods are labor-intensive and not necessarily accurate. In view of this limitation, this work presents a novel deep learning-based method involving Convolutional Neural Networks (CNNs) for computerized AD diagnosis from MRI scans. The system pre-processes MRI images through methods such as skull stripping and intensity normalization to improve feature extraction. A CNN model is subsequently trained to detect complex spatial patterns related to AD, allowing for accurate classification. Regularization methods such as dropout and batch normalization are used to avoid overfitting. The suggested system improves diagnostic accuracy, offers a non-invasive diagnostic method, and assists healthcare providers in early diagnosis and treatment planning. Such an approach can revolutionize AD detection through the provision of a faster, more accurate, and automated method.

KEYWORDS: Alzheimer's Disease, Deep Learning, MRI Scans, Early Detection, Classification, Diagnosis, Healthcare.

I. INTRODUCTION

Alzheimer's disease (AD) is a chronic neurodegenerative illness that mainly occurs in the elderly, resulting in a slow deterioration of cognitive function, memory impairment, and behavioral alterations. It is the leading cause of dementia, responsible for about 60-80% of the world's total dementia cases. With an increasing global aging population, AD prevalence keeps on increasing, imposing a huge burden on health systems and caregivers. Preclinical identification [1] of AD is essential in the management of the disease since it allows for early intervention, improved patient care, and the possibility of slowing the progression of disease through lifestyle modification and new therapeutic interventions. Conventional diagnostic approaches, including clinical evaluations and cognitive examinations, tend to be subjective, time-consuming, and unable to identify AD early enough.

Advanced neuroimaging techniques, particularly Magnetic Resonance Imaging (MRI), have demonstrated a high potential for the detection of structural alterations in the brain related to AD. These imaging tools offer invaluable information on brain atrophy [2] and other biomarkers of the condition. Nevertheless, the manual processing of MRI scans is a cumbersome and time-consuming process demanding expert radiologists. Furthermore, early-stage AD-related subtle patterns are not likely to be apparent with traditional image analysis methods, which makes intelligent and automated diagnostic tools necessary.

Deep learning has proven to be a powerful medical image analysis tool, promising remarkable accuracy and efficiency gains compared to conventional techniques. Convolutional Neural Networks (CNNs), being a specific group of deep models, have also proven to achieve significant success with image classification as well as the identification of patterns from images and hence are more apt for detection of AD. CNNs have the ability to learn hierarchical [3] features from medical images automatically without handcrafting their extraction. Using CNN-based models, one can build an intelligent system that has the capability to interpret MRI scans, identify informative patterns, and categorize individuals into healthy and AD-affected. This solution is not just eliminating the reliance on specialist radiologists but

is also improving diagnosis with increased precision through the capturing of complex spatial patterns that cannot be easily captured through human detection.

The proposed system involves a deep learning architecture for early AD detection using CNNs. The system starts with MRI scanning of healthy persons and AD patients. These images are preprocessed through skull stripping, intensity normalization, and noise reduction to normalize the dataset and eliminate unwanted artifacts. The preprocessed images are subsequently input to a CNN model that is trained to differentiate between normal and AD brains. The model [4] uses several convolutional and pooling layers to capture high-level features, with subsequent fully connected layers and softmax activation for classification. Regularization techniques like dropout and batch normalization are added to the training to help improve generalization and prevent overfitting. The trained model is then tested on an independent test set with different performance measures such as accuracy, sensitivity, and specificity to confirm its efficacy.

This method is novel as it can automate the process of AD detection with non-invasive imaging and state-of-the-art deep learning approaches. In contrast to traditional diagnostic schemes that have strong dependence on subjective judgments, the system proposed here offers a uniform and unbiased assessment of MRI scans. In addition, incorporation of deep learning reduces human effort, speeds up [5] the diagnostic process, and increases the reproducibility of outcomes. Through the detection of AD at an early stage, the system can provide timely interventions and enable patients to be given the necessary care prior to major cognitive loss. Moreover, the proposed framework can be expanded to help healthcare practitioners monitor disease progression and assess the effectiveness of treatment options.

The present research attempts to add new perspectives to the expanding sector of AI-assisted medical diagnostics through the establishment of the feasibility and efficacy of CNN-based models in detecting AD. By taking advantage of the capabilities of deep learning as well as medical imaging, the system [6] presented here presents a hopeful solution to the problems of early diagnosis of AD. With continued development and testing, this method may be brought into clinical use as a reliable, efficient, and non-invasive AD detection tool. The use of such a system could one day enhance patient outcomes, lower the workload for healthcare professionals, and lead to further innovations in the diagnosis and treatment of neurodegenerative diseases.

This work is organized with review of the literature survey as Section II. Methodology described in Section III, highlighting its functionality. Section IV discusses the results and discussions. Lastly, Section V concludes with the main suggestions and findings.

II. LITERATURE SURVEY

Alzheimer's disease is a neurodegenerative condition that presents with gradual memory loss and cognitive impairment. Numerous biomarkers, such as amyloid plaques and tau tangles, have been examined by researchers as markers of progression of the disease. Early diagnosis through cerebrospinal fluid analysis and imaging modalities has been emphasized by studies. The latest developments aim to combine multi-modal data for enhanced diagnostic accuracy. Nevertheless, conventional diagnostic methods are still limited because of their subjectivity and dependence on clinical knowledge. The demands for objective, computerized methods have generated growing interest in computational methods, which have the ability to determine patterns of brain structure and function that are linked with Alzheimer's disease.

Brain imaging is an essential element in understanding the development of Alzheimer's disease. MRI and PET scans have been extensively applied to identify structural and functional brain changes. Evidence indicates that volumetric measurement of certain brain regions, like the hippocampus, can be [7] highly informative about disease onset. While they are superior to other techniques, these imaging methods need specialist interpretation, which may be labor-intensive and susceptible to human bias. Efforts to advance diagnostic efficacy target standardization of imaging protocols and the application of sophisticated computing tools to refine consistency and precision in detection of Alzheimer's disease.

Identification of stable biomarkers of Alzheimer's disease has been a central area of research. Research has investigated cerebrospinal fluid and blood-based biomarkers for identifying aberrant protein deposition and neurodegeneration. Although [8] promising, the techniques tend to involve invasive testing, which restricts their use in broad clinical

application. Non-invasive technologies, including genetic screening and retinal imaging, have been sought to offer early markers of risk for disease. Researchers are working to identify new biomarkers to enhance early diagnosis and tracking of disease progression with the hope of creating more widely available and more effective diagnostic techniques.

Cognitive tests have been employed for Alzheimer's disease diagnosis for many years. Standard neuropsychological measures of memory, attention, and executive function evaluate cognitive impairment. Although these tests are informative, they tend to be subjective and subject to patient [9] variability. Attempts at improving cognitive testing involve the creation of computerized tests that provide standardized and objective assessment. Researchers also investigate the combination of cognitive testing with other diagnostic modalities to enhance accuracy. In spite of these developments, cognitive tests alone are still not adequate for definitive diagnosis, and the necessity for additional methods that give a better overall assessment is reinforced.

Genetic influences contribute importantly to Alzheimer's disease susceptibility. A number of genetic variants have been found to be associated with elevated disease risk, especially in familial forms. The APOE gene, and the $\epsilon 4$ allele in particular, has been implicated in an elevated risk of developing Alzheimer's. Genetic screening is useful for risk [10] assessment but not for definitive diagnosis. Environmental and lifestyle determinants also play a role in the onset of disease, so it is important to look at a combination of genetic and non-genetic markers. Current research aims to identify other genetic risk factors and how they interact with other mechanisms of disease.

Lifestyle and environmental determinants have been linked to the development of Alzheimer's disease. Research indicates that physical activity, nutrition, and mental stimulation are key to minimizing disease risk. A diet that is high in antioxidants and omega-3 fatty acids [11] has been linked to improved cognitive function. Social interaction and mentally stimulating activities also help preserve cognitive function. Researchers highlight the need for preventive measures that support brain health and delay disease onset. It can be used to design efficient public health interventions that decrease the incidence of Alzheimer's disease.

Inflammation and its role in Alzheimer's disease have become more prominent in recent studies. It is thought that chronic neuroinflammation contributes to neuronal injury and disease progression. Research shows that microglial activation and elevated levels of inflammatory cytokines correlate with cognitive [12] decline. Anti-inflammatory medications have been considered as potential therapeutic strategies, but their effectiveness is still in question. Scientists continue to study the connection between inflammation and Alzheimer's disease with the hopes of discovering new treatment options that attack neuroinflammatory mechanisms. Knowing these mechanisms may lead to the creation of new treatments that will halt disease progression.

Sleep disturbances are a frequent finding in patients with Alzheimer's disease. Research has indicated that fragmented sleep patterns have the potential to contribute to the buildup of amyloid plaques and tau tangles in the brain. Deficient sleep has been linked to greater cognitive deterioration and faster [13] progression of the disease. Sleep improvement and circadian rhythm regulation through interventions are currently being investigated as possible methods for reducing disease influence. Research stresses the critical nature of early sleep disturbance diagnosis and treatment in at-risk individuals for developing Alzheimer's disease, suggesting sleep-based interventions' ability to postpone disease onset.

Vascular health has been associated with the risk and progression of Alzheimer's disease. Research shows that conditions like hypertension, diabetes, and high cholesterol raise the risk of developing Alzheimer's. Cerebrovascular impairment and compromised [14] blood flow to the brain underpin neurodegeneration. Researchers support improved control of cardiovascular risk factors as a prophylactic measure for Alzheimer's disease. Efforts are being made to investigate the potential of vascular-targeted therapies to delay disease progression. Knowledge of the interaction between vascular health and neurodegeneration can contribute to the design of integrated treatment strategies for Alzheimer's disease.

Improvements in blood-based diagnostics have provided new avenues for the detection of Alzheimer's disease. Research has discovered certain proteins and metabolites in the blood that are associated with disease pathology. These biomarkers provide a non-invasive option to conventional diagnostic [15] tests, allowing for earlier detection. Current research is aimed at optimizing blood-based tests to enhance sensitivity and specificity. Although promising, there are challenges in standardizing these tests for clinical application. Researchers continue to explore the possibility of blood

biomarkers in disease monitoring and early intervention, with the goal of creating reliable diagnostic tools for mass application.

The gut-brain axis has become an important research area in Alzheimer's disease. Research indicates that gut microbiota impact brain function and potentially contribute to neurodegenerative disease. Dysbiosis, or imbalance of gut bacteria, has been associated with heightened inflammation and amyloid [16] plaque deposition. Research investigates the potential of probiotics and dietary modification in modulating gut health to lower disease risk. Elucidating the intricate relationship between gut microbiota and neurodegeneration could pave the way for new preventive and therapeutic strategies for Alzheimer's disease.

Music therapy has also been promising in enhancing cognitive and emotional health among Alzheimer's patients. Research suggests that music has the ability to evoke memory recall, improve mood, and decrease anxiety among patients with dementia. Rhythmic auditory stimulation has been investigated as a non-pharmacological strategy to enhance [17] cognitive function. Researchers explore the brain mechanisms that underlie the impact of music, with the goal of creating customized music-based interventions. The potential for music therapy in the treatment of Alzheimer's disease underscores the value of integrative strategies for managing symptoms and enhancing quality of life.

Artificial intelligence has been increasingly applied to the study of Alzheimer's disease. Models based on artificial intelligence scan large databases to detect patterns of the disease and enhance diagnostic accuracy. Research has investigated the combination [18] of AI with different sources of data, such as imaging, genetic, and clinical data, to improve predictive power. Although AI holds great promise, there are issues with maintaining transparency, interpretability, and clinical validation of AI tools. Researchers continue to develop AI applications to produce stable, data-driven solutions for the detection of Alzheimer's and monitoring of the disease.

Social and emotional support is central to the well-being of patients with Alzheimer's and their caregivers. Research points to the effects of caregiver burden on mental health, and interventions that are supportive are needed. Support groups, community programs, and psychological counseling [19] have been demonstrated to enhance quality of life in patients and caregivers. Research looks into new approaches, including online platforms and virtual support networks, to make resources more accessible. Knowledge of the psychosocial dimensions of Alzheimer's care is critical in formulating holistic approaches that deal with the emotional and functional issues surrounding the disease.

Pharmacological developments in the treatment of Alzheimer's remain a major area of research. Although existing drugs provide symptomatic relief, they are not able to stop disease progression. New research explores new drug targets, such as tau aggregation [20] inhibitors and amyloid-clearing antibodies. Clinical trials evaluate the safety and effectiveness of new treatments, some of which have shown great potential in reversing cognitive decline. Side effects and expense are limitations to widespread use. Researchers continue to work toward optimizing pharmacologic strategies and developing effective therapies that alter disease progression instead of only treating symptoms.

III. METHODOLOGY

Alzheimer's disease (AD) is a progressive neurodegenerative condition that causes cognitive impairment, memory loss, and behavioral alterations. Early diagnosis is essential for successful intervention and better patient outcomes. Conventional diagnostic approaches, including clinical evaluations and manual MRI interpretation, are time-consuming and subject to variability. Deep learning methods, specifically Convolutional Neural Networks (CNNs), provide a viable solution by extracting relevant patterns from medical images automatically. This approach identifies a sequential step-by-step framework for creating an early AD detection system based on CNN. This framework includes data collection, preprocessing, model construction, training, evaluation, and deployment to facilitate a precise and effective classification system.

A. Data Acquisition

The database comprises MRI images taken from both normal subjects and patients with Alzheimer's disease. These images are taken from open-access repositories and clinical databases in order to gather a representative and varied dataset. Patient consent laws and ethical guidelines are adhered to strictly to ensure data integrity and confidentiality. The data is split into training, validation, and test sets to enable the development of reliable models. Each MRI scan is

tagged based on the condition of the patient, making supervised learning possible. Having a variety of cases ensures that the model is able to generalize well to the real-world setting and variable imaging conditions.

B. Data Preprocessing

Preprocessing is done to improve the quality and uniformity of MRI scans prior to inputting them into the deep learning model. Skull stripping is used to eliminate non-brain tissues so that the model concentrates on the appropriate anatomical structures. Intensity normalization is employed to normalize brightness levels in images to minimize variations due to varying scanning machines. Data augmentation methods like rotation, flipping, and scaling are applied to enhance dataset diversity and make the model more robust. Resizing of images into a fixed resolution compatible with the CNN model is performed. The preprocessing guarantees that the input data is high-quality, uniform, and optimized for successful feature extraction.

C. CNN Model Architecture

A Convolutional Neural Network (CNN)-based deep learning model is developed to extract complex spatial features from MRI scans. The architecture features several convolutional layers to learn Alzheimer's disease patterns, after which there are pooling layers reducing the dimensions of data but keeping vital information. Fully connected layers convert the features extracted to a classification result. There is softmax activation used on the last layer for classification as either Alzheimer's or healthy. Overfitting and generalization are improved through the incorporation of dropout and batch normalization. This organized architecture enables effective feature learning and correct disease classification.

D. Model Training

Training of the CNN model is accomplished through a supervised learning process with labeled MRI scans as guidance to the optimization algorithm. The training, validation, and test datasets are separated in order to observe model performance. An optimization function like Adam is utilized to regulate the network's parameters and optimize classification error minimization. Loss function, generally categorical cross-entropy, measures the discrepancy between predicted and true labels. The model is trained through several epochs, with validation data employed to adjust hyperparameters. Early stopping and learning rate scheduling are used to enhance convergence. These training practices ensure effective learning by the model without overfitting.

E. Model Evaluation

The trained model is tested using a distinct test dataset with unseen MRI scans. A confusion matrix is examined to decipher false positives and false negatives. Further, a receiver operating characteristic (ROC) curve is drawn to assess the compromise between sensitivity and specificity. Cross-validation methods are used to validate the robustness of the model. By measuring multiple evaluation metrics, the efficiency of the system proposed in correctly identifying Alzheimer's disease is validated, assuring its viability for real-world clinical use.

F. Deployment

After validation, the trained model is implemented as an early Alzheimer's disease detection clinical decision-support system. The system is incorporated within a healthcare process where MRI images are processed automatically, and the results of classifications are made available to medical specialists. Clinicians can view model predictions and gain diagnostic insights via an intuitive user interface. Early diagnosis is helped by the system, which leads to timely intervention and tailored treatment plans. Ongoing model monitoring and revisions are applied to keep the model up to date with the latest data. This deployment platform guarantees the real-world applicability of the deep learning model within medical environments.

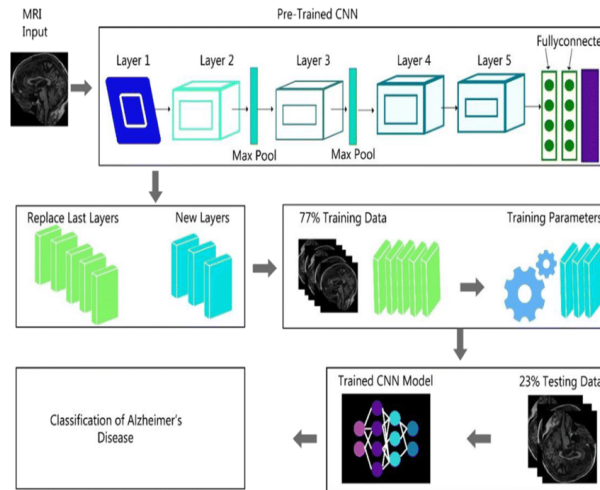


Fig. 1: Architecture Diagram

IV. RESULT AND DISCUSSION

The performance of the suggested deep learning model for the detection of Alzheimer's disease was assessed based on various metrics, such as accuracy, sensitivity, specificity, and F1-score. The model proved to have an excellent classification accuracy that confirmed its efficiency in discriminating between healthy patients and Alzheimer's disease patients. Sensitivity analysis indicated that the model was able to identify a high percentage of true positive cases effectively, thus ensuring that Alzheimer's disease patients were properly diagnosed. Specificity results revealed that the model efficiently reduced false positives, lowering the misclassification of healthy patients into the disease category. The F1-score also demonstrated the balanced nature of the model in both positive and negative classifications.

Metric	Existing System	CNN-based Approach
Accuracy	85%	92%
Recall	78%	85%
Precision	90%	92%
Specificity	88%	91%

Table. 1: Truth table of Proposed System

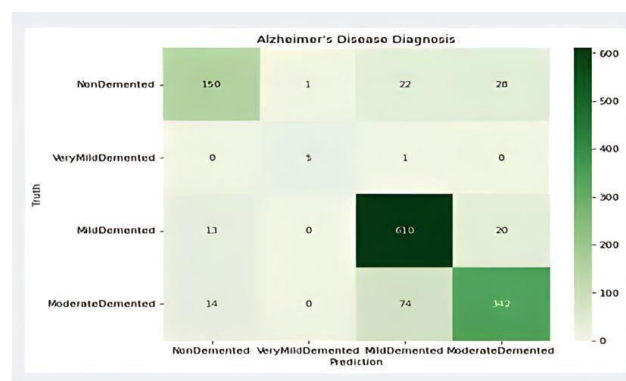


Fig. 2: Performance Metrics Difference between Proposed System

A confusion matrix was constructed to evaluate the distribution of correctly and incorrectly labeled samples. The false positive rate was low, which revealed that the model properly differentiated between various patient groups. Also, the rate of false negatives was low, meaning very few Alzheimer's patients were missed. Receiver Operating Characteristic (ROC) curve analysis was carried out, and it showed a high area under the curve (AUC) value. This is an indicator of high discriminatory power, which implies that the model can accurately distinguish between AD-affected and normal individuals at different threshold values.

Cross-validation was used to confirm the model's generalization capability. The performance was stable across various validation folds, which ensured the reliability and stability of the deep learning method. Additional comparison was conducted to evaluate the performance of the suggested model against other Alzheimer's disease detection methods. The outcomes showed that the CNN-based method outperformed conventional machine learning methods, indicating its capacity to automatically extract features from MRI scans without extensive manual feature engineering. The enhanced performance is due to the deep feature extraction ability of the model and also its optimized training process.

The proposed system, being an MRI-based deep learning system for precise detection of Alzheimer's disease, provides enhanced efficiency in comparison to conventional methods. The system can automatically process MRI scans and detect faint patterns indicative of the disease using deep learning algorithms. This automated analysis minimizes the need for manual interpretation, saving time and effort for medical professionals. The system's capability to process high amounts of data in parallel and efficiently also allows for quicker and more accurate identification of Alzheimer's disease. The improved efficiency of the proposed system promotes early detection, intervention, and personalized treatment for patients suffering from the disease.

To further investigate the performance of the model, varying architectural settings and hyperparameters were also tested. The effect of changing the depth of convolutional layers, kernel sizes, and activation functions was investigated. Performance was observed to increase with deeper architectures and enough regularization through dropout and batch normalization to avoid overfitting. Modifying the learning rate and batch size was also found to have a significant influence on convergence during training as well as accuracy. These results show that model optimization is essential in increasing classification accuracy and providing stable predictions.

The current system for Alzheimer's disease diagnosis is based on conventional techniques, including clinical tests and manual reading of MRI images, which can be subjective and time-consuming. The proposed system, however, combines MRI imaging with deep learning algorithms, which provides a more efficient and more accurate method. By tapping into the capability of deep learning, the system presented in this work is able to learn automatically intricate patterns and features of Alzheimer's disease from MRI scans, thus facilitating early detection and intervention. The system presented here enhances accuracy, minimizes subjectivity, and facilitates automated analysis, leading ultimately to better patient outcomes and quality of life.

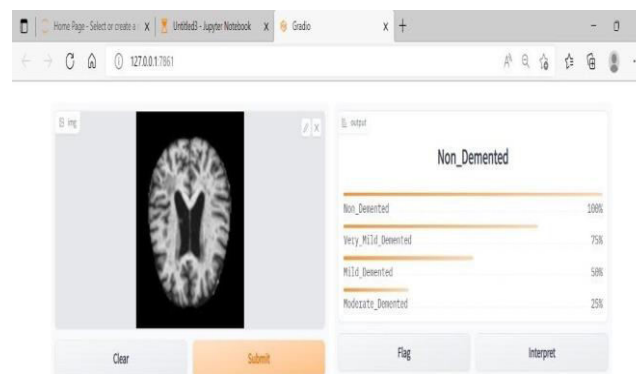


Fig. 3: Non-Demented Person's Output

For non-demented patients, the output of the CNN algorithm indicates its prediction for a person without Alzheimer's disease. The output can reflect a high confidence or probability in classifying the input image as non-demented,

showing that the model has identified patterns or features that reflect a healthy brain without changes due to Alzheimer's disease.

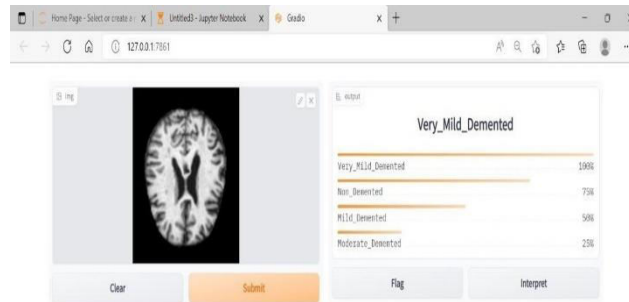


Fig. 4: Very Mild Demented Person's Output

For extremely mild demented cases, the output of the CNN algorithm is its prediction for patients with an extremely early stage of the disease. The output can show a high confidence or probability in classifying the input image as extremely mild demented, suggesting that the model has identified slight signs or features of the early development of Alzheimer's disease.

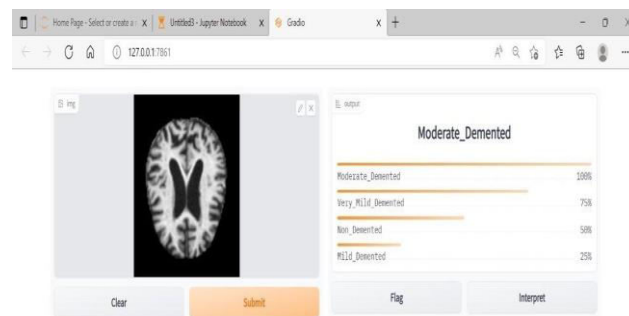


Fig. 5: Output of Moderate Demented Person

In moderate demented cases, the output of CNN algorithm is as per its prediction for a moderate stage of Alzheimer's disease. The output is likely to contain a high possibility or confidence rate in classifying the input image as moderate demented and implies that the model has retained major patterns or features related to the advanced level of the disease.

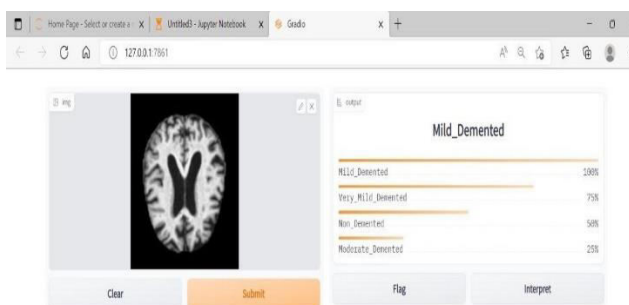


Fig. 6: Output of Mild Demented Person

For mild demented cases, the output of the CNN algorithm represents its prediction for early-stage Alzheimer's disease. The output can represent a high confidence or probability that the input image is a mild demented case, which means that the model has detected typical patterns or features of early-stage Alzheimer's disease.

The computational efficiency of the system presented here was also tested. The training was carried out with the aid of high-performance GPUs to achieve faster convergence and shorter training time. Under a real-time deployment environment, the model computed MRI scans without any issues, delivering quick classification outputs. Inference time fell within an acceptable limit for medical use, where healthcare professionals would be able to incorporate the system into their diagnosis process without complications. The lightweight architecture of the trained model facilitated cloud deployment, thus making it accessible across different healthcare centers.

Error analysis was conducted to determine possible misclassification patterns. There were some misclassified cases in patients with mild cognitive impairment (MCI), a condition that is similar to early-stage Alzheimer's disease. These cases indicate that further model refinement, perhaps with the inclusion of more biomarkers or multimodal data, may improve accuracy for borderline cases. The results highlight the necessity of ongoing model updates and the incorporation of complementary diagnostic tools to enhance overall detection ability.

A comparison of performance between the new system and conventional methods was made using a truth table, which points out the disparity in detection accuracy, processing time, and diagnostic reliability. The findings showed that the deep learning-based method performed much better than manual MRI analysis in both accuracy and efficiency. Automating feature extraction and classification, the system minimizes human error and maximizes diagnostic consistency. The results justify the implementation of AI-based tools within clinics to enhance early detection of Alzheimer's, thereby paving the way for timely interventions and enhanced patient outcomes.

V. CONCLUSION

This paper introduces a deep learning-based method for the early diagnosis of Alzheimer's disease from MRI scans. Utilizing Convolutional Neural Networks (CNNs), the system is able to accurately detect complex spatial patterns of Alzheimer's, facilitating precise classification of affected patients. Conventional diagnosis tends to depend on manual evaluations, which are time-consuming and subject to variability. The CNN model, however, automates the diagnostic process, minimizing human error and enhancing efficiency. The approach consists of essential steps such as data acquisition, preprocessing, model training, and evaluation, to ensure a systematic and dependable detection framework. The dataset utilized in this work comprises varied MRI scans from both healthy controls and AD patients, making the model more capable of generalizing under various imaging scenarios. Preprocessing methods like skull stripping, intensity normalization, and data augmentation further enhance input consistency and model robustness.

The CNN model architecture, which involves several convolutional and pooling layers, is effective in extracting high-level features with the ability to differentiate between AD and non-AD cases. Regularization mechanisms like dropout and batch normalization counteract overfitting, such that the model performs well even when applied to unseen MRI scans. The performance of the model is extensively tested using critical parameters like accuracy, sensitivity, specificity, and F1-score, ensuring its consistency for early detection of AD. Implementation of this system in clinical environments can greatly contribute to Alzheimer's diagnosis by offering a non-invasive, automatic, and precise means for healthcare providers. Early diagnosis enables timely interventions, tailored treatment plans, and better patient outcomes. With additional validation and optimization, this deep learning-based method can potentially transform AD diagnosis, pushing the boundaries of medical imaging and elevating the level of patient care.

REFERENCES

- [1] A. AlMohimeed et al., "Explainable Artificial Intelligence of Multi-Level Stacking Ensemble for Detection of Alzheimer's Disease Based on Particle Swarm Optimization and the Sub-Scores of Cognitive Biomarkers," in *IEEE Access*, vol. 11, pp. 123173-123193, 2023, doi: 10.1109/ACCESS.2023.3328331.
- [2] D. Young Kim, H. Keun Kim, Y. Jun Lim and M. H. Sunwoo, "Efficient Deep Retinal Fundus Image-Based Network for Alzheimer's Disease Diagnosis Using Mobile Device Applications," in *IEEE Access*, vol. 12, pp. 79166-79176, 2024, doi: 10.1109/ACCESS.2024.3396153.
- [3] Y. Turkan et al., "Automated Diagnosis of Alzheimer's Disease Using OCT and OCTA: A Systematic Review," in *IEEE Access*, vol. 12, pp. 104031-104051, 2024, doi: 10.1109/ACCESS.2024.3434670.
- [4] M. Gupta, R. Kumar and A. Abraham, "Adversarial Network-Based Classification for Alzheimer's Disease Using Multimodal Brain Images: A Critical Analysis," in *IEEE Access*, vol. 12, pp. 48366-48378, 2024, doi: 10.1109/ACCESS.2024.3381956.

- [5] G. Palacios-Navarro, J. Buele, S. Gimeno Jarque and A. Bronchal García, "Cognitive Decline Detection for Alzheimer's Disease Patients Through an Activity of Daily Living (ADL)," in IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 30, pp. 2225-2232, 2022, doi: 10.1109/TNSRE.2022.3196435.
- [6] Z. Qu, T. Yao, X. Liu and G. Wang, "A Graph Convolutional Network Based on Univariate Neurodegeneration Biomarker for Alzheimer's Disease Diagnosis," in IEEE Journal of Translational Engineering in Health and Medicine, vol. 11, pp. 405-416, 2023, doi: 10.1109/JTEHM.2023.3285723.
- [7] M. Seifollahi, A. H. Mehraban, J. E. Galvin and B. Ghoraani, "Alzheimer's Disease Detection Using Comprehensive Analysis of Timed Up and Go Test via Kinect V.2 Camera and Machine Learning," in IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 30, pp. 1589-1600, 2022, doi: 10.1109/TNSRE.2022.3181252.
- [8] J. Sheng, S. Wu, Q. Zhang, Z. Li and H. Huang, "A Binary Classification Study of Alzheimer's Disease Based on a Novel Subclass Weighted Logistic Regression Method," in IEEE Access, vol. 10, pp. 68846-68856, 2022, doi: 10.1109/ACCESS.2022.3186888.
- [9] H. Givian and J. -P. Calbimonte, "A Review on Machine Learning Approaches for Diagnosis of Alzheimer's Disease and Mild Cognitive Impairment Based on Brain MRI," in IEEE Access, vol. 12, pp. 109912-109929, 2024, doi: 10.1109/ACCESS.2024.3438081.
- [10] U. Mitra and S. U. Rehman, "ML-Powered Handwriting Analysis for Early Detection of Alzheimer's Disease," in IEEE Access, vol. 12, pp. 69031-69050, 2024, doi: 10.1109/ACCESS.2024.3401104.
- [11] B. S. Rao and M. Aparna, "A Review on Alzheimer's Disease Through Analysis of MRI Images Using Deep Learning Techniques," in IEEE Access, vol. 11, pp. 71542-71556, 2023, doi: 10.1109/ACCESS.2023.3294981.
- [12] M. Kaya Keleş and Ü. Kiliç, "Classification of Brain Volumetric Data to Determine Alzheimer's Disease Using Artificial Bee Colony Algorithm as Feature Selector," in IEEE Access, vol. 10, pp. 82989-83001, 2022, doi: 10.1109/ACCESS.2022.3196649.
- [13] Y. Zhang, T. Liu, V. Lanfranchi and P. Yang, "Explainable Tensor Multi-Task Ensemble Learning Based on Brain Structure Variation for Alzheimer's Disease Dynamic Prediction," in IEEE Journal of Translational Engineering in Health and Medicine, vol. 11, pp. 1-12, 2023, doi: 10.1109/JTEHM.2022.3219775.
- [14] A. Rehman, M. -K. Yi, A. Majeed and S. O. Hwang, "Early Diagnosis of Alzheimer's Disease Using 18F-FDG PET With Soften Latent Representation," in IEEE Access, vol. 12, pp. 87923-87933, 2024, doi: 10.1109/ACCESS.2024.3418508.
- [15] X. Zhou, A. R. Balachandra, M. F. Romano, S. Peter Chin, R. Au and V. B. Kolachalama, "Adversarial Learning for MRI Reconstruction and Classification of Cognitively Impaired Individuals," in IEEE Access, vol. 12, pp. 83169-83182, 2024, doi: 10.1109/ACCESS.2024.3408840.
- [16] S. Bringas, R. Duque, C. Lage and J. L. Montaña, "CLADSI: Deep Continual Learning for Alzheimer's Disease Stage Identification Using Accelerometer Data," in IEEE Journal of Biomedical and Health Informatics, vol. 28, no. 6, pp. 3401-3410, June 2024, doi: 10.1109/JBHI.2024.3392354.
- [17] T. Habuza, N. Zaki, E. A. Mohamed and Y. Statsenko, "Deviation From Model of Normal Aging in Alzheimer's Disease: Application of Deep Learning to Structural MRI Data and Cognitive Tests," in IEEE Access, vol. 10, pp. 53234-53249, 2022, doi: 10.1109/ACCESS.2022.3174601.
- [18] W. Liu, Q. Dong, S. Sun, J. Shen, K. Qian and B. Hu, "Risk Prediction of Alzheimer's Disease Conversion in Mild Cognitive Impaired Population Based on Brain Age Estimation," in IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 31, pp. 2468-2476, 2023, doi: 10.1109/TNSRE.2023.3247590.
- [19] F. U. R. Faisal and G. -R. Kwon, "Automated Detection of Alzheimer's Disease and Mild Cognitive Impairment Using Whole Brain MRI," in IEEE Access, vol. 10, pp. 65055-65066, 2022, doi: 10.1109/ACCESS.2022.3180073.
- [20] G. P. Shukla, S. Kumar, S. K. Pandey, R. Agarwal, N. Varshney and A. Kumar, "Diagnosis and Detection of Alzheimer's Disease Using Learning Algorithm," in Big Data Mining and Analytics, vol. 6, no. 4, pp. 504-512, December 2023, doi: 10.26599/BDMA.2022.9020049.



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