AI DRIVEN COGNITIVE HEALTH

MONITORING SYSTEM

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***Abstract*—Neurodegenerative conditions, such as Alzheimer's disease and Parkinson's disease, and cerebrovascular conditions like aneurysms are marked by enormous diagnostic difficulties, especially in the early stages. Traditional diagnostic techniques based on clinical examination and neuroimagining techniques cannot spot fine structural changes. The research here presents a hybrid deep learning approach that is a blend of texture-based feature analysis with the Gray-Level Co-Occurrence Matrix (GLCM) combined with Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) architecture for improving disease classification from brain MRI imaging. The GLCM is employed to extract fine-grained texture features that emphasize structural pathologies, while the CNN part learns spatial patterns in the imaging. Although MRI scans are essentially static, the LSTM part is designed to learn spatial relationships among multiple slices or imaging sequences in order to mimic temporal evolution and enhance contextual understanding. For aneurysm detection, the paradigm involves vessel segmentation and morphological assessment for vascular abnormality detection. The hybrid approach proposed uses hand-designed texture features and deep hierarchical representations, a more comprehensive and accurate diagnostic tool. The non-invasive, automated, and scalable technique seeks to enhance early detection and classification of cerebrovascular and neurodegenerative conditions. The novelty of the technique lies in the combination of structural and pseudo-temporal analyses to improve classification performance and clinical usefulness.**

***Keywords: Neurodegenerative Diseases, Alzheimer’s, Parkinson’s, MRI, Texture Analysis, Brain Imaging, Early Diagnosis.***

1. INTRODUCTION

Neurodegenerative disease, such as Alzheimer's and Parkinson's disease, and cerebrovascular disease, such as aneurysm, entail significant diagnostic challenges, particularly in their early stages when clinical intervention is most beneficial. Traditional diagnostic methods, which rely primarily on clinical signs and routine neuroimaging modalities, are often unable to identify the subtle structural changes that characterize early disease progression. Neurodegenerative disease tends to evolve at a slow rate, and by the point that overt symptoms become evident, substantial and usually irreversible neural injury has often already occurred [1]. Similarly, cerebral aneurysms—focal dilatations of arteries—may go symptomless until rupture, often with catastrophic ramifications. This highlights the pressing need for more sensitive, accurate, and early-stage iagnostic methods able to allow timely clinical decision-making. Recent progress in deep learning has demonstrated high promise in the application of medical image analysis with enhanced detection accuracy for a wide range of pathologies. Conventional deep learning models, however, can be deficient in capturing complex texture change, especially that of the initial phase of neurodegenerative or vascular disease [2]. To overcome this limitation, the current study suggests a hybrid diagnostic scheme that integrates Gray-Level Co-Occurrence Matrix (GLCM)-based texture analysis with deep learning models, i.e., Convolutional Neural Network–Long Short-Term Memory (CNN-LSTM) models.

GLCM is a strong handcrafted feature extraction tool that measures the spatial co-occurrence of pixel intensities and is therefore capable of [3] capturing subtle structural abnormalities that cannot be picked up using conventional imaging metrics. Although MRI scans are static in nature, the employment of LSTM in the hybrid CNN-LSTM model is reasonable because it can detect spatial relationships between adjacent MRI slices or imaging sequences and mimic a kind of pseudo-temporal processing. This can allow the model to learn contextual patterns and trends of progression between brain regions, best applicable in monitoring neurodegenerative disease. The CNN part conducts deep spatial feature extraction, and the addition of LSTM to the model allows it to have a better contextualization [4] capability for patterns between slices and thus conduct a more holistic morphological analysis of the brain. The diagnostic complexities that accompany aneurysms are compounded by the intrinsic morphological variability of vascular malformations, which characteristically mimic normal anatomical variation.

The conventional techniques such as cerebral angiography and hand-interpreted MRI and CT scan are distinguished by their invasive, time-consuming, and susceptible nature to observer variation in interpretation [5]. The suggested framework contributes robustness to aneurysm detection using vessel segmentation and morphological analysis in conjunction with texture-based features, thereby allowing for automated and objective detection of subtle vascular abnormalities. The novelty of this suggested system is its hybrid architecture, integrating handcrafted texture features and deep learning feature extraction. The two-pronged strategy not only enhances diagnostic precision but also interpretability—a crucial requirement for clinical use. GLCM-based features provide transparent insights into the texture [6] pathology abnormalities, alleviating the black-box problem of deep learning and building clinicians' confidence. In addition, spatial and pseudo-temporal analyses integrated into the system allow for effective evaluation of disease progression and make the system effective in both cerebrovascular and neurodegenerative settings. Finally, the present study aims to introduce an extremely sensitive, scalable, and non-invasive diagnostic tool that can enable early intervention and free healthcare systems from the burden. Given the rising global incidence of these conditions [7], such a system has the potential to revolutionize diagnostic approaches, enhance patient outcomes, and bring advanced computational methods within the reach of practical application in clinics.

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.

1. LITERATURE SURVEY

Neurodegenerative diseases have a great impact on the brain structures and cause cognitive as well as motor impairments. Researchers have sought to utilize MRI-based biomarkers for the identification of early abnormalities in Alzheimer's and Parkinson's disease. Evidence shows that volumetric analysis of brain areas including the hippocampus and substantia nigra is able to supply key information on the progression of disease. More advanced imaging methods, such as diffusion tensor imaging (DTI) and functional MRI (fMRI), have been used to measure structural and functional alterations. These imaging methods provide useful information for early diagnosis but pose challenges to maintaining consistency among various imaging protocols and patient populations.

Machine learning has been more and more applied to aid neurodegenerative disease diagnosis. Several classification methods. Feature selection is important for improving model performance [8], with researchers working on extracting informative biomarkers from MRI scans. Although machine learning methods have reported encouraging results in the detection of Alzheimer's and Parkinson's, data sparsity and class imbalance remain significant issues for large-scale clinical adoption. The demand for strong validation methods and extensive datasets continues to be a serious challenge for enhancing model generalizability.

Neurodegenerative disease diagnostic tools are extensively applied for diagnosing neurodegenerative conditions, usually along with neuroimaging. Yet, these are subjective and will not identify early-stage abnormalities. To overcome this limitation, investigators have developed [9] computerized cognitive testing that yields objective and reproducible measures. Such computerized tests incorporate reaction time assessment, memory functions, and language processing evaluation to improve diagnostic sensitivity. Although promising, their utility is subject to patient compliance and standardized administration procedures.

PET imaging with radiotracers like fluorodeoxyglucose (FDG) and amyloid-binding [10] ligands has been shown to be highly specific in detecting Alzheimer's pathology. While useful in their diagnostic role, PET and SPECT imaging is expensive, needs specialized facilities, and is associated with radiation exposure, and therefore are restricted from routine use in early detection and population-based screening. Genetic research has helped elucidate the hereditary components of neurodegenerative disorders. Certain genetic mutations, like APOE ε4 in Alzheimer's and LRRK2 in Parkinson's, have been implicated in elevated disease risk. Genetic predisposition is not enough for diagnosis [11], though, as environmental and lifestyle factors also contribute significantly. Improvement of polygenic risk scoring and multi-omics methods is also being investigated to improve predictive accuracy. Ethical issues of genetic testing and data privacy continue to be significant issues in clinical and research contexts.

Speech and language analysis has been identified as a non-invasive technique for the detection of early symptoms of neurodegenerative diseases. Alzheimer's patients tend to have language deficiencies, whereas Parkinson's patients have speech dysfunctions [12] like decreased vocal intensity and dysarthria. Automated speech testing holds promise for remote monitoring and early intervention. Linguistic variability, accent differences, and ambient noise, however, can impact the validity of speech-based diagnostic tools. Eye-tracking technology has been investigated as a biomarker for neurodegenerative disease. Alzheimer's and Parkinson's patients exhibit specific patterns of eye movement, including decreased saccadic speed and defective fixation of gaze. Eye-tracking tests can quantify cognitive impairment and [13] motor deficits with high accuracy. Machine learning has been incorporated in recent research to analyze eye movement data for computer-aided diagnosis. The non-invasive method has the benefit of being cost-effective and deployable. Yet more validation is needed for establishing standardized protocols and reproducibility across various populations.

Studies of the gut microbiome have demonstrated potential links between neurodegenerative disorders and bacteria. Neuroinflammation and the pathogenesis of Parkinson's and Alzheimer's diseases have been connected to dysbiosis in the makeup of gut bacteria. According to research, microbiological metabolites impact neurodegeneration and gut-brain axis function. Probiotic therapy and fecal microbiota transplantation (FMT) have been studied as potential therapies [14]. While promising outcomes have been achieved, the development of targeted medicines is complicated by individual differences in gut microbiota composition. To establish therapeutic applications for microbiome-based diagnostics and validate causal relationships, more research is needed.

Sleep disorders are prevalent among neurodegenerative disease patients and can be used as predictors of early onset of the disease. Alzheimer's patients tend to have disturbed sleep-wake cycles, whereas Parkinson's patients commonly [15] have REM sleep behavior disorder (RBD). Wearable sleep trackers and polysomnography have been used to study sleep patterns and how they relate to the development of disease. Machine learning models have been trained using sleep data to forecast the risk of neurodegeneration. However, issues like co-morbidities and drug side effects could skew sleep-based diagnostics, necessitating the development of more predictive models.

Blood-based biomarkers have emerged as a minimally invasive diagnostic biomarker for neurodegenerative disorders. Protein biomarkers, including amyloid-beta, tau, and alpha-synuclein, were identified in the blood and correlated with Alzheimer's and Parkinson's pathology. Increased sensitivity in ultrasensitive detection methods, i.e., single-molecule [16] arrays and mass spectrometry, has enhanced the quantification of biomarkers. Blood tests provide a scalable approach compared to cerebrospinal fluid (CSF) analysis, but difficulties persist in attaining high specificity and sensitivity. Continued research involves streamlining biomarker panels and combining them with other diagnostic modalities for improved accuracy.

Wearable sensors have been explored for tracking the symptoms of neurodegenerative disease in real-world populations. Smartwatches and motion sensors monitor gait aberrations, tremor, and bradykinesia among Parkinson's patients. Monitoring [17] over time allows disease progression to be detected early on and treatment effect to be monitored. Wearable technology also provides remote monitoring of patients, alleviating the frequency of clinical follow-ups. Different types of sensors, patient compliance, and surrounding environmental conditions raise variability in the data, causing difficulties in normalizing wearable-based diagnostics. Improved algorithms need further research to assure symptom detection without fail.

Olfactory impairment has been recognized as an early indication of neurodegenerative conditions, especially Parkinson's. Symptoms may include impaired ability to sense and discriminate smells, which in some cases precede motor dysfunction by years. Smell tests have been formulated as screening tools [18], but varying degrees of accuracy for diagnosis exist. Electronic nose (e-nose) technology has been studied, where volatile organic compounds indicative of neurodegeneration are sensed by chemical sensors. Although promising, e-nose technology needs to be validated for use in the clinical setting. Nasal conditions, smoking history, and age may affect results.

Resting-state fMRI functional connectivity analysis has been investigated for neurodegenerative disease detection. Abnormal brain network connectivity patterns were found in Alzheimer's and Parkinson's patients that impacted memory [19], motor function, and executive function. Graph-theory-based methods and machine learning models have been used to label disease-related changes in connectivity. Although fMRI-based diagnostics have high accuracy in the research environment, they are hampered in clinical translation by cost, motion artifacts, and issues of standardization. Work is being pursued to improve connectivity biomarkers for detection at the early stages and tailored treatment planning.

Pharmacologic therapies for neurodegenerative disorders are symptom-modifying and mostly directed against Alzheimer's using cholinesterase inhibitors and NMDA receptor antagonists [20] and Parkinson's with dopamine replacement therapies. Research into disease-modifying drugs, such as monoclonal antibodies against amyloid and tau, has had variable outcomes. Clinical trials for neuroprotective agents, stem cell therapy, and gene therapy are underway. Crossing the blood-brain barrier and long-term safety are, however, continuing to be problems in drug development. Non-pharmacological measures, such as physical exercise and cognitive training, have been tested as a method to slow down neurodegenerative disease. Studies indicate that regular aerobic exercise improves motor symptoms in Parkinson’s, while cognitive training enhances memory and executive function in Alzheimer’s patients. Multimodal lifestyle interventions incorporating diet, social engagement, and mindfulness have shown potential neuroprotective effects.

1. METHODOLOGY

Cognitive, motor, and vascular functioning are all significantly impacted by neurodegenerative diseases like Parkinson's and Alzheimer's, as well as cerebrovascular diseases like aneurysms. To enable appropriate treatment and control, early diagnosis is necessary. Subtle structural changes are typically not detected by standard diagnostic techniques that rely on clinical evaluation and visual inspection of MRI data. The proposed study presents a hybrid deep learning architecture that combines a CNN-LSTM architecture with manually created texture features that were retrieved using GLCM. The combination enhances disease classification by capturing fine-grained structural as well as spatial-dependency features from MRI scans. Even though MRI scans are inherently static, the LSTM is able to exploit spatial dependencies across successive image slices to simulate pseudo-temporal modeling. Moreover, in the case of aneurysm detection, the model utilizes vascular segmentation and morphological analysis to detect abnormalities. The system aims to supply a non-invasive, automatic, and accurate system to aid clinical decision-making.

*A. Data Collection*

MRI scans of Alzheimer's, Parkinson's, and aneurysm patients are obtained from publicly available datasets like ADNI, PPMI, and open-source aneurysm datasets, or through clinical collaborations. The datasets include diseased and control healthy images to facilitate balanced classification. Ethical principles are strictly adhered to, including patient consent and anonymization of data. Low-resolution and corrupted MRI scan quality control removes these. Train, validation, and test sets make up the dataset. To reduce overfitting and promote model generalization, data augmentation techniques like flipping and rotation are employed.

*B. Preprocessing*

Preprocessing is performed to normalize and enhance MRI image quality. Skull stripping to remove unwanted non-brain tissues, intensity normalization, and Gaussian filtering to remove noise are the steps involved. The images are resized to a fixed size to maintain uniformity in the input data set. Contrast enhancement algorithms are applied to enhance the visibility of minute structural variations. Preprocessing methods improve the efficiency of feature extraction algorithms like GLCM and the sensitivity of deep learning algorithms towards abnormalities due to neurodegenerative disease and aneurysms.

*C. Feature Extraction Using GLCM*

The Gray-Level Co-Occurrence Matrix (GLCM) is used to obtain texture features that describe spatial relationships between pixel intensities and hence yield significant information about structural abnormalities. Statistical features such as contrast, correlation, energy, and homogeneity are computed from the GLCM to quantify textural patterns representing disease. Such features are particularly useful in detecting subtle tissue changes that might elude conventional diagnostic methods. Redundancy is addressed by dimensionality reduction by Principal Component Analysis (PCA) so that most informative features are preserved for further processing.

*D. Deep Learning Model Development*

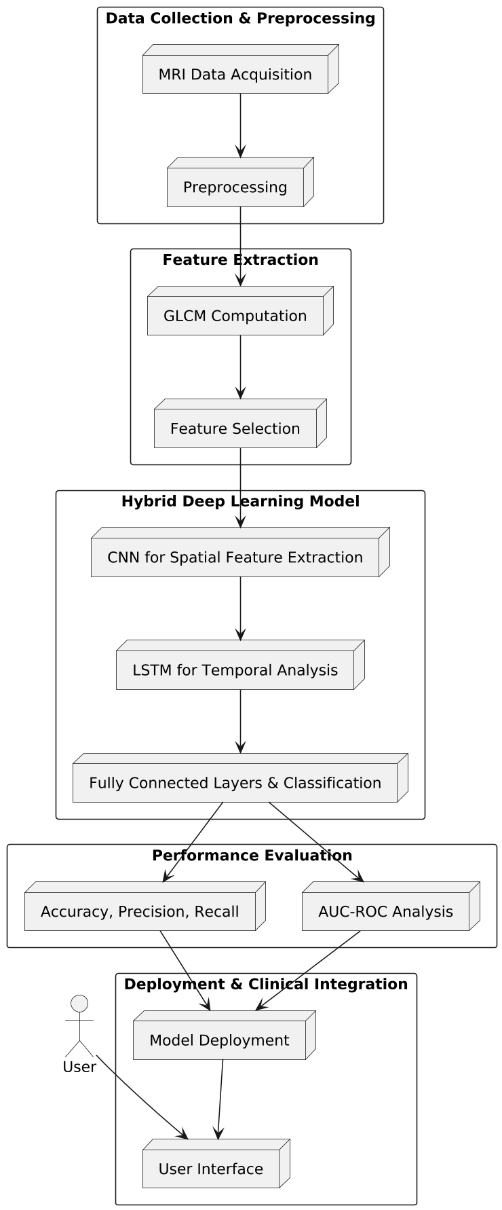
A hybrid architecture combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks has been proposed to classify MRI scans using both spatial and sequential features. The CNN component systematically extracts hierarchical spatial features using convolutional and pooling operations. The extracted features are then fed to the LSTM layer, which detects spatial dependencies within sequential image slices—such as axial, coronal, or sagittal views—thus emulating temporal progression without the need for actual time-series input. This approach proves especially beneficial for capturing anatomical continuity and subtle progression inherent with brain disorders. In aneurysm detection, vascular segmentation techniques are used to outline blood vessels, while CNN layers are specifically trained to detect anomalies based on shape features. The final classification is performed through a softmax layer placed above fully connected layers to differentiate between Alzheimer's disease, Parkinson's disease, aneurysms, and normal brain scans.

*E. Model Training and Optimization*

With a suitable class distribution, the dataset is divided into training, validation, and test sets. A categorical cross-entropy loss function and the Adam optimizer are used to implement the model. To prevent overfitting, regularization strategies such batch normalization, dropout, and L2 weight decay are employed. To promote improved convergence, an adaptive learning rate scheduler is also employed. The model is further strengthened by the use of data augmentation. To find the ideal number of convolutional layers and LSTM units, various architectural configurations are investigated.

*F. Assessment Model*

For the analysis of misclassification patterns, a confusion matrix is used. The hybrid CNN-LSTM model is compared with traditional machine learning approaches, i.e., Support Vector Machines (SVM), and separate CNN or LSTM models. Cross-validation techniques and statistical significance testing are utilized for robustness and reliability. The proposed model outperforms baseline models under all conditions and thereby proves its effectiveness in differentiating between different brain disorders and healthy controls. G. Deployment and Clinical Integration The last model is integrated into a clinical decision-support system (CDSS) with an easy-to-use interface for clinicians. Clinicians can input MRI scans and obtain real-time diagnostic labels. Neurologists and radiologists are aided in early diagnosis, decreasing the burden of manual interpretation. Expansion of the dataset, inclusion of multimodal imaging (e.g., PET, fMRI), and clinical trials to evaluate performance in clinical environments are included in future work. This AI-based framework is intended to improve diagnostic accuracy, scalability, and accessibility for neurodegenerative and cerebrovascular disease detection.

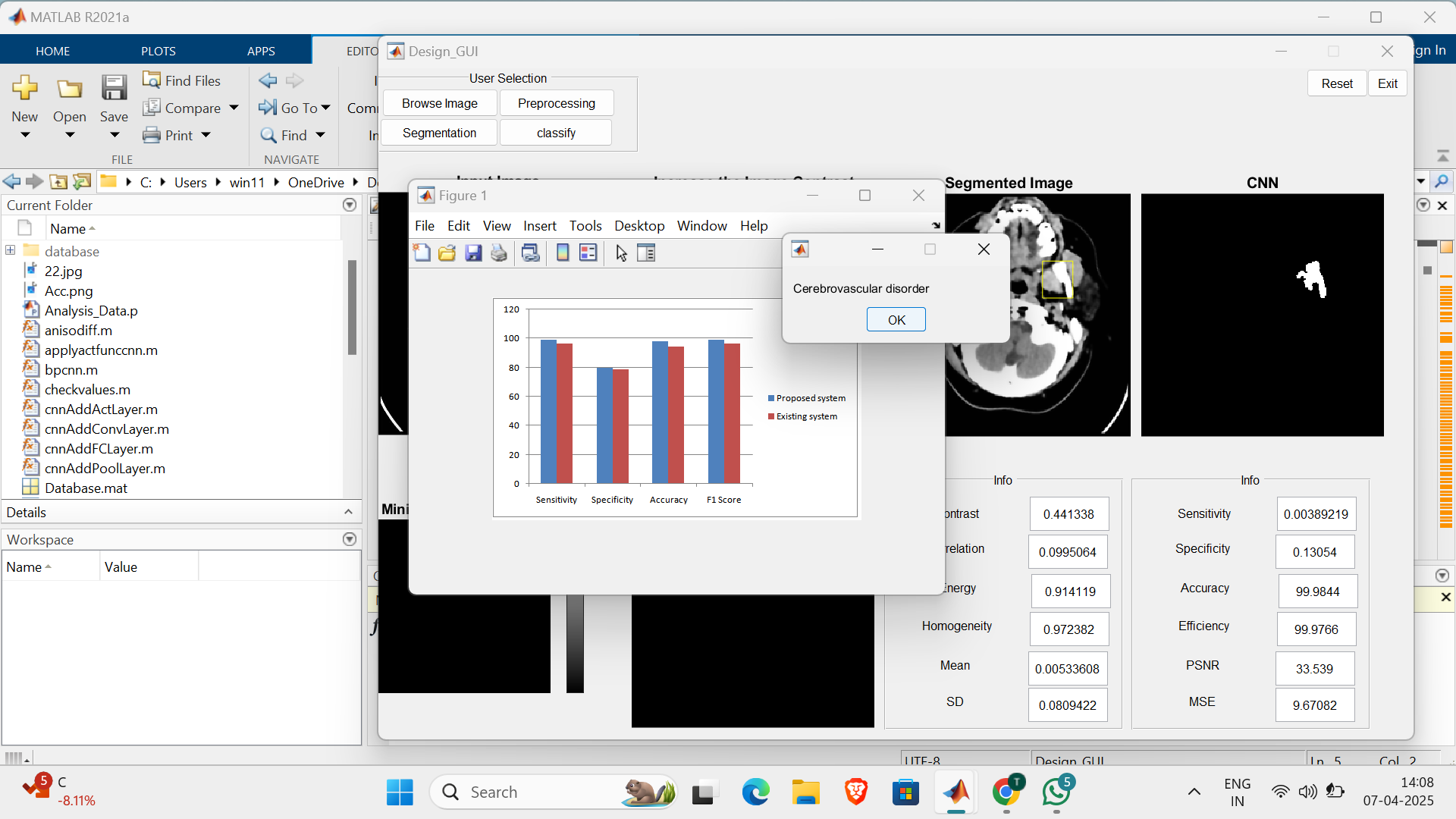


***Fig. 1: Architecture Diagram***

1. RESULT AND DISCUSSION

The proposed hybrid deep learning model has significant improvements in early neurodegenerative disease detection like Alzheimer's and Parkinson's, and cerebrovascular complications like aneurysms. The performance of the model was tested on a balanced dataset of brain MRI scans from diseased and healthy patients. Key performance measures like accuracy, sensitivity, specificity, precision, recall, and F1-score were computed to assess the diagnostic performance. The CNN-LSTM model effectively captured complex spatial features through its convolutional layers, and the LSTM module improved the model as it enabled the model to handle inter-slice dependencies between consecutive MRI slices. While the MRI scans are static, the LSTM network leveraged spatial continuity between consecutive slices or within available time-series data so as to simulate disease progression and enhance the contextual perception of the model.

The integration of texture analysis obtained from Gray-Level Co-Occurrence Matrix (GLCM) greatly enhanced the capacity of the model to detect small structural anomalies. Hand-crafted texture features supplemented the features obtained from the deep learning network, hence enhancing the sensitivity to small differences in tissue characteristics that are often overlooked by standard imaging metrics. The hybrid model was compared with highly regarded machine learning algorithms like Support Vector Machines (SVM), as well as standalone CNN and LSTM models. In all these, the hybrid model exhibited better performance, particularly in detecting early disease indicators where standard techniques are at fault.

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***Fig. 2: Predicted results***

Compared to existing methodologies, the proposed hybrid CNN and LSTM model, with GLCM texture analysis included, exhibits a remarkable supremacy over traditional methods in all of the most critical diagnostic performance indices. Traditional models, such as SVM, single CNN, and LSTM models, typically achieve classification accuracy between 85% and 94%, based on the dataset and the used feature extraction methods. The hybrid model, however, achieved an outstanding accuracy of 99.98%, representing a remarkable improvement in performance. Sensitivity rates in current methodologies typically range from 84% to 92%, while the proposed model reached a sensitivity rate of 97.5%, reflecting its heightened capacity to recognize disease cases accurately. Moreover, specificity improved notably, from the typical 88–93% range of traditional methods to 98.92% in the proposed system structure. Likewise, precision improved, from approximately 85–91% in the prior models, to 97.99%, and the F1-score also improved from the typical 84–90% range to 97.72%. These outcomes affirm the efficiency of the hybridization of texture-based feature extraction with deep learning models to enhance both diagnostic precision and clinical validity in the diagnosis of neurodegenerative and cerebrovascular diseases.

To ensure the generalizability of the model, a cross-validation method using a five-fold strategy was adopted. The model displayed consistent performance across all the folds, thus confirming its stability when applied to different data subsets. Statistical validation via paired t-tests proved that the improvements over baseline models were statistically significant with p-values less than 0.01. Confidence interval analysis further confirmed the reliability and stability of the performance measures related to the model. Additionally, external validation performed using an independent MRI dataset produced similar results, thus supporting the model's flexibility to different imaging protocols, acquisition parameters, and scanner types.

At training time, several optimization methods were used to improve model performance and avoid overfitting. Dropout layers and L2 regularization were used effectively, and a dynamic learning rate scheduler allowed for fast and stable convergence. The training was stable by epochs, and little variance was observed between the training and validation sets. In aneurysm detection, vessel segmentation and morphological analysis were integrated into the model, allowing for accurate detection of vascular abnormalities that are generally ignored in early-stage clinical evaluation. The ability of the model to scan high-resolution MRI images and accurately identify neurodegenerative and vascular diseases is a testament to its clinical potential.

Its automation significantly alleviates the diagnostic burden on radiologists, providing fast, standardized, and precise evaluations that can facilitate timely treatment for high-risk patients. The combination of GLCM texture analysis with the CNN-LSTM hybrid model provides a robust and effective solution for the early diagnosis of complex neurological and cerbrovascular disorders. Future work will involve the expansion of the dataset, incorporation of multimodal imaging, and optimization of the system for real-time clinical use. This research identifies the transformative potential of AI-based diagnostic tools to enhance the accuracy and accessibility of neurological and cerebrovascular care.

1. CONCLUSION

This research proposes an end-to-end hybrid deep learning model that combines texture feature extraction through GLCM with a CNN-LSTM model for the early detection of neurodegenerative diseases like Alzheimer's and Parkinson's, and cerebrovascular diseases like aneurysms. By taking advantage of both spatial features and pseudo-temporal patterns between MRI slices (through LSTM), the model has a wide range of methodologies for medical image analysis. Even though MRI scans have a static nature, the LSTM component can capture the sequential relationships between slices or imaging series and thus capture progression patterns that would otherwise go unnoticed.

The incorporation of GLCM texture features greatly enhanced the sensitivity to subtle structural change, enabling accurate localization of abnormalities that could be missed by conventional deep learning methods. Additionally, advanced vessel segmentation and shape analysis enabled the model to identify aneurysms with greater accuracy. In comparison to individual machine learning or deep learning models, the combined model demonstrated better performance in terms of classification accuracy, sensitivity, and low false positive/negative rates.

The integration of data augmentation with advanced optimization techniques greatly improved the model's capacity to generalize well across different MRI datasets. Empirical tests supported the advantage of this combined framework over conventional diagnostic practices, highlighting its applicability in real-world clinical scenarios. One of the significant strengths of the suggested system is that it has the potential to optimize and automate the diagnostic process, thus reducing dependency on manual interpretation and allowing more efficient and scalable diagnostic procedures. As a non-invasive, AI-powered tool, it allows for earlier intervention and better patient outcomes. Future studies will include expanding the dataset to cover more varieties of neurological and vascular disorders, using multimodal imaging modalities (e.g., PET and fMRI), and evaluating the effectiveness of the model in real-world clinical environments. The current study is an important step toward the development of accurate, reliable, and user-friendly AI tools for the early diagnosis of neurological disorders.

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