Enhanced Diagnosis of Alzheimer's Disease through Predictive Progression Analysis of Neuro Imaging Sequences

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***Abstract*— Alzheimer's disease is an inevitable and progressive neurodegenerative disorder that may still prove challenging to diagnose accurately in its early stages. The currently available techniques that enable diagnosis based on either neuroimaging or clinical assessments are relatively late at the time of detection, which never facilitates proper intervention. The study describes a novel deep learning framework based on the principle of the combination of CNNs and LSTM networks towards enhanced early diagnosis of AD. Exploiting the CNNs for spatial feature extraction from medical imaging data, and with LSTMs capturing temporal patterns that describe what could happen to characterize the progression of neurodegenerative changes, gives the proposed approach the ability to analyze both structural and sequential aspects of the disease, thus providing a more extended diagnosis. Improvement of diagnostic accuracy to allow for much earlier detection of Alzheimer's with simplification of treatment plans using the hybrid model CNN-LSTM. This work will contribute to the development of more effective AI-driven diagnosis of better prediction and management of Alzheimer's disease, which will eventually show improvement in patient outcomes.**

I. INTRODUCTION

Alzheimer's disease is one of the neurodegenerative disorders that afflict millions of people worldwide. The progress of Alzheimer's is marked by continually losing memories and a decline in cognitive abilities. It is the most common cause of dementia in older adults, with the burden of the disease growing as populations age. Early intervention is critical in the management of Alzheimer's disease, as it allows for timely intervention and slows the progression of the disease, thereby providing patients with an enhanced quality of life. However, recent diagnostic approaches-including clinical assessment, neuroimaging methodologies, and biomarker analysis-will often identify disease only at the moderate to advanced stage of its illness. Furthermore, these techniques are only moderately efficient in detecting early-stage AD, thus confining their efficacy in prognosis and treatment planning. Artificial intelligence and machine learning, more broadly, have, of late proven hopeful promises of new developments in the improvement of accuracy and timeliness in the diagnosis of Alzheimer's disease. Deep learning seems particularly promising in the analysis of very complex data sets: medical images, clinical records, and genetic information. Convolutional Neural Networks are one of the subdivisions of deep learning models that have been of great use in medical images. It is with such models of CNNs that find its application in neuroimaging, such as magnetic resonance imaging. The disease is characterized not only by spatial changes but also by the development of some temporal patterns over time due to Alzheimer's disease.

To address this complexity, we propose a novel deep learning approach combining the strengths of CNNs and Long Short-Term Memory (LSTM) networks. CNNs are suited well to capture spatial features from neuroimaging data, such as structural brain changes, while LSTMs excel in handling sequential data with long-term dependencies for processing temporal information. This integration of CNNs and LSTMs in a hybrid model allows for the simultaneous examination of both spatial and temporal features, giving a more comprehensive insight to the underlying disease processes.

This hybrid model is expected to improve the early detection of Alzheimer's disease by leveraging the complementary nature of CNNs and LSTMs. A CNN might be used to focus on determining very highly informative structural changes in the brain--for instance, patterns of atrophy associated with Alzheimer's--while LSTMs are often used to model the progression of those changes over time, capturing the temporal dynamics essential for distinguishing early-stage Alzheimer's from normal aging. The proposed model will strongly enhance the ability to analyze these complex data patterns, thereby enhancing the scope of their diagnostic accuracy. The model has the capability to revolutionize the early diagnosis of Alzheimer's disease.. Additionally, the false positives and negatives would be reduced when the predictions become more reliable, thus enhancing reliability in early diagnosis. With it, the hybrid CNN-LSTM model could be on the road to screening tools that could eventually improve early intervention, thus mitigating the impact of Alzheimer's disease on patients and their families in the long run.

CNNs and LSTMs are impressive integrations in deep learning that overcome the deficiencies of the clinical methods used for diagnosis. This model hybridizes the strengths of analyzing spatial features from medical images and temporal features in medical data to bring forward a challenging early and accurate Alzheimer's disease diagnosis challenge. The key to this paper is to evaluate AI-driven diagnostic tools for the benefit of individuals at risk of developing Alzheimer's disease.

II. Literature Survey

The integration of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks proves effective in analyzing brain imaging data. CNNs capture structural features in the data, while LSTMs provide temporal sequence analysis, refining diagnostic tools and improving accuracy. Additionally, Generative Adversarial Networks (GANs) generate synthetic data to better train machine-based algorithms and enhance predictive usefulness in longitudinal studies of individuals with Dementia or Alzheimer's Disease. This combined approach can contribute to more precise and accurate diagnoses of dementia and its neurodegenerative forms. I am particularly interested in exploring how the complementary nature of CNN and LSTM can provide more informative accounts of the changes to cognition resulting from Alzheimer's disease.

From the paper [1]Liao et al proposed that a new wireless 16-channel electroencephalography (EEG) system with dry spring-loaded sensors can improve the comfort and reliability of EEG measurements without the need for conductive gels or skin preparation. In their methodology, they designed a 16-channel EEG system using dry, spring-loaded sensors to measure brain activity. The system is wireless, enhancing convenience and mobility. The system's performance was validated by comparing its signal quality with traditional wet sensors. The results showed that the dry sensor system performed comparably to wet sensors in terms of signal quality, making it a viable alternative.From paper [2] C. A. Lane, J. Hardy, and J. M. Schot proposed an overview of Alzheimer’s disease, including its clinical features, pathology, and potential treatments. In their methodology, they conducted a comprehensive review of the literature, summarizing findings on genetics, pathology, and clinical presentation, while also discussing diagnostic criteria The results showed the complexity of Alzheimer’s disease, including the interplay of genetic and environmental factors, and highlighted the need for more research.

From paper [3] C. L. Masters, R. Bateman, K. Blennow, et al proposed a detailed primer on Alzheimer’s disease, discussing molecular and genetic factors In their methodology, they synthesized research on disease mechanisms and current treatments The results showed a broad understanding of Alzheimer’s progression and the limitations of current treatments, emphasizing early intervention and from paper [4] **M. S. Kamal, A. Northcote, L.Chowdhury,etal** proposed an analysis of Alzheimer’s disease patients using imaging and gene expression data with explainable AI (XAI) techniques to identify associated genes. In their methodology, they used imaging data and gene expression data, applying AI techniques to find associations. The results showed that the model identified key genes linked to Alzheimer’s and provided explanations for their roles in disease progression and from paper [4] From the paper C. Trigona et al proposed the use of AI to analyze Alzheimer’s disease, focusing on gene-disease associations.In their methodology, they applied imaging and gene data analysis with AI techniques The results showed that the AI model successfully identified relevant genes associated with Alzheimer’s and From the paper [6] P. Scheltens et al, This review explores Alzheimer’s disease, emphasizing its clinical manifestations, pathophysiology, diagnostic challenges, and treatment options. The authors conducted an extensive review of existing research, synthesizing findings from clinical trials, observational studies, and meta-analyses to provide a broad overview of the disease. Their methodology focuses on integrating data from various sources to highlight key challenges in early diagnosis and the mixed success of current treatment approaches, particularly in addressing the underlying causes of Alzheimer’s. The review sheds light on the complex nature of Alzheimer’s, emphasizing the multifactorial interactions involved in its progression and the inherent difficulties in developing universally effective therapeutic interventions. The results underline the importance of continued research in identifying reliable diagnostic biomarkers and advancing therapeutic strategies aimed at slowing disease progression, while also addressing the global public health impact of the disease.

From the paper [7] J. Wiley ,This paper offers a statistical analysis of Alzheimer’s disease, focusing on its prevalence, societal impact, and the associated healthcare costs. The authors provide an in-depth examination of data sourced from epidemiological studies, national surveys, and healthcare system databases, offering insights into the growing burden of Alzheimer’s on public health systems globally. Methodologically, the study compiles and interprets data from multiple sources to present a cohesive picture of the current and future trends in Alzheimer’s disease prevalence, economic strain, and resource allocation. The results reveal concerning statistics, such as the rapidly increasing number of diagnosed cases as populations age, along with the immense economic burden this poses on healthcare systems and families. The paper calls attention to the urgent need for more comprehensive healthcare planning and policy interventions to mitigate the anticipated future impact of Alzheimer’s disease on both patients and society. From the paper [9] F. J. Martinez-Murcia, A. Ortiz, J.-M. Gorriz, J. Ramirez, and D. Castillo-Barnes ,This study explores the manifold structure of Alzheimer’s disease through the use of advanced convolutional autoencoders to analyze brain imaging data. The authors aim to improve both the understanding and the early diagnosis of Alzheimer’s by leveraging unsupervised deep learning techniques to extract meaningful features from imaging data, specifically focusing on how these features can represent different stages of the disease’s progression. The methodology involves training convolutional autoencoders on large datasets of brain scans, which helps in identifying underlying patterns that may otherwise be overlooked through traditional imaging analysis methods. The results demonstrate that the model was able to effectively capture the complex, multi-dimensional nature of Alzheimer’s disease, enabling improved classification accuracy of the disease’s progression stages. This novel approach suggests that autoencoders and deep learning techniques can significantly contribute to better diagnostic tools for Alzheimer’s and other neurodegenerative diseases and From the paper [8] Y. Guo, Y. Gao, and D. Shen proposed a novel method for prostate segmentation in magnetic resonance (MR) images, which combines deep feature learning with sparse patch matching to enhance the accuracy of deformable image segmentation. The authors address a critical challenge in medical imaging, where accurate segmentation is essential for effective diagnosis and treatment planning. Their methodology involves training a deep learning model to extract relevant features from MR images, followed by the application of sparse patch matching to deformably segment the prostate. This two-step approach allows the model to capture both global and local image structures, improving the overall segmentation accuracy. The results show that the proposed method outperforms traditional segmentation techniques, offering superior accuracy and robustness, particularly in dealing with variations in patient anatomy. This advancement could lead to more precise diagnostic outcomes and better treatment planning for prostate-related conditions.

From the paper [10] H. T. Shen et al present a data fusion-based approach to predict the conversion from mild cognitive impairment (MCI) to Alzheimer’s disease using heterogeneous data sources. This study leverages machine learning techniques to integrate and analyze multiple types of data, including imaging, clinical records, and genetic information, aiming to improve the accuracy of predictions related to MCI conversion. The methodology involves training machine learning models on this fused data to identify complex patterns and markers indicative of the progression from MCI to Alzheimer’s disease. The results demonstrate that this heterogeneous data fusion approach significantly outperforms models that rely on single-modality data, providing more reliable and accurate predictions. The paper highlights the potential of integrating diverse data sources in enhancing predictive models, ultimately contributing to earlier diagnosis and more personalized treatment strategies for patients at risk of Alzheimer’s. From the paper [11] X. Jiang, L. Zhang, L. Qiao, and D. Shen proposed a method to estimate functional connectivity networks in the brain by employing a low-rank tensor approximation technique. The focus of their study is on identifying mild cognitive impairment (MCI), a condition that often precedes Alzheimer’s disease. Their approach aims to capture the complex network of functional connectivity patterns in the brain, which undergo alterations in individuals with MCI. By modeling these changes, they seek to enhance early diagnosis and intervention opportunities. In their methodology, the authors applied the low-rank tensor approximation technique to model the functional connectivity networks of the brain. This approach reduces the dimensionality of the data while preserving the critical connectivity patterns relevant to cognitive functionality. The model was designed to specifically identify MCI by analyzing these altered connectivity patterns in patients, enabling a more focused diagnostic process. The results showed promising findings, with the paper likely reporting key metrics such as classification accuracy, sensitivity, and specificity for the identification of MCI. These metrics are critical for validating the effectiveness of the model. However, the exact numbers and detailed findings would need to be referenced directly from the paper for precise evaluation.

From the paper[12] J.-H. So, N. Madusanka, H.-K. Choi, B.-K. Choi, and H.-G. Parkfocused their research on improving the classification of Alzheimer’s disease through the use of deep learning models. Their work specifically involves analyzing texture features extracted from medical images, with the goal of enhancing the accuracy of Alzheimer’s disease diagnosis. Texture analysis is a crucial aspect of medical image interpretation, as it can reveal subtle structural differences in the brain that are associated with disease progression. In their methodology, the authors employed deep learning techniques to extract and analyze texture features from brain imaging data. By training the model on these texture features, they aimed to develop a robust classifier that could distinguish between healthy brains and those affected by Alzheimer’s disease. The use of deep learning allowed the model to automatically learn and identify relevant features from the data, reducing the need for manual feature selection. The results demonstrated that the deep learning model achieved high accuracy in classifying Alzheimer’s disease based on texture features. This outcome highlights the potential of deep learning in medical image analysis, particularly for complex conditions like Alzheimer’s disease. The success of this model suggests that incorporating texture features into diagnostic workflows could significantly improve the early detection and classification of the disease.

From the paper [13]Z. Zhang et al. introduces a novel task-driven hierarchical attention network (THAN) designed for diagnosing mild cognitive impairment (MCI) and Alzheimer’s disease using medical images. The attention mechanism in neural networks allows models to focus on specific parts of the input data that are most relevant to the task at hand. The authors leverage this capability by designing a hierarchical structure where different layers of the model focus on various aspects of the medical images, improving the model's ability to extract meaningful diagnostic features. In their methodology, the authors developed a hierarchical attention network that processes medical images through multiple layers. Each layer of the network is designed to focus on different features of the data, allowing the model to capture both high-level and detailed information about brain structure and function. Additionally, the task-driven nature of the model enables it to adapt its attention mechanism depending on whether the task is diagnosing MCI or Alzheimer’s disease. This adaptability makes the model versatile and suitable for different diagnostic challenges. The results showed that the THAN model outperformed traditional diagnostic methods in identifying MCI and Alzheimer’s disease. This demonstrates the effectiveness of the hierarchical attention mechanism, which allows the model to better capture the subtle differences in brain images associated with these conditions. The success of this approach could lead to more accurate and earlier diagnoses, ultimately improving patient outcomes.

From the paper [14]K. Kwak, H. J. Yun, G. Park, and J.-M. Lee tackled the challenge of Alzheimer’s disease classification by employing a multi-modality approach. They integrated data from multiple sources, such as MRI and PET scans, and used sparse representation techniques to improve classification accuracy. Multi-modality approaches are increasingly important in medical diagnosis, as they combine different types of data to provide a more comprehensive understanding of the disease. Sparse representation, in particular, helps to reduce the dimensionality of the data while preserving the most informative features, leading to more accurate and efficient models. In their methodology, the authors utilized a sparse representation approach to integrate and analyze the multi-modality data (e.g., MRI, PET) for Alzheimer’s disease classification. Sparse representation reduces the complexity of the data by focusing on the most relevant features, allowing the model to process large amounts of information without becoming overwhelmed by irrelevant details. This approach is particularly useful in medical imaging, where large datasets can be challenging to manage effectively. The results indicated that the multi-modality sparse representation approach significantly improved the classification accuracy of Alzheimer’s disease compared to using single-modality data. This suggests that combining data from multiple sources provides a more complete picture of the disease, leading to better diagnostic performance. The use of sparse representation also enhances the model's efficiency, making it a valuable tool for clinical applications.

From the paper [15]**Error! Reference source not found.** M. Liu, D. Zhang, E. Adeli, and D. Shen introduces a multiview learning approach aimed at improving the diagnosis of Alzheimer’s disease. The authors propose leveraging multitemplate feature representation to capture the complex and heterogeneous nature of the data. Alzheimer’s disease is a multifaceted condition, and a single-view approach often fails to capture all relevant aspects of the disease. By using a multiview approach, the authors seek to improve diagnostic accuracy by integrating information from multiple sources. In their methodology, the authors developed a multiview learning framework that integrates multiple views of the data, such as different imaging modalities (e.g., MRI, PET) and clinical features. This approach allows the model to consider various aspects of the disease, providing a more comprehensive analysis. Additionally, the multitemplate feature representation technique was used to capture the complex structure of the data, which is essential for understanding the heterogeneous nature of Alzheimer’s disease. The results demonstrated that the multiview learning approach significantly improved diagnostic accuracy compared to traditional single-view methods. This success highlights the importance of considering multiple perspectives when diagnosing complex diseases like Alzheimer’s. The multiview approach not only enhances accuracy but also provides a more nuanced understanding of the disease, which could lead to better treatment strategies.

From the paper [16] R. R. Selvaraju, M. Cogswell, A. Das, R. Vedantam, D. Parikh, and D. Batraintroduced Grad-CAM, a technique aimed at generating visual explanations for deep learning models. The goal of Grad-CAM is to make the decision-making process of deep neural networks more interpretable by visually highlighting the important regions in an input image that contribute to the model's output. Interpretability has become a significant concern in the field of deep learning, especially when models are applied in critical areas such as healthcare. By improving the transparency of these models, Grad-CAM helps users better understand how a model arrives at its decisions. The methodology employed by the authors involves using gradient information to identify and produce visual explanations. Grad-CAM is applicable to various deep learning architectures, including convolutional neural networks (CNNs), and works by backpropagating the gradients associated with a specific class to the convolutional layers of the network. This is resulting in gradient-based heatmap highlights the important areas in the input image. This technique enhances the interpretability of deep learning models across different domains. The results demonstrated that Grad-CAM successfully provided visual explanations for a variety of deep learning models, significantly improving transparency and interpretability. The technique is versatile and can be used across multiple architectures, making it a valuable tool for improving the trustworthiness of AI systems.

From the paper [17] Y. Zhao, B. Ma, P. Jiang, D. Zeng, X. Wang, and S. Li presented a novel approach to predicting Alzheimer’s disease progression through the use of a Multi-Information Generative Adversarial Network (MI-GAN). Accurate prediction of disease progression is crucial for timely interventions and effective treatment planning in Alzheimer’s disease. The MI-GAN framework aims to improve prediction accuracy by integrating multi-modal information, such as brain imaging and clinical data, into a unified predictive model. In their methodology, the authors designed a generative adversarial network (GAN) that incorporates multiple sources of data, leveraging the power of adversarial learning to enhance prediction capabilities. The MI-GAN framework fuses multi-modal information, allowing the model to capture the complex interactions between different data types. By combining imaging data, clinical features, and other relevant information, the MI-GAN model aims to predict the trajectory of Alzheimer’s disease more accurately than traditional methods. The results showed that the MI-GAN approach led to significant improvements in predicting Alzheimer’s disease progression. The integration of multi-modal data enhanced the model's ability to make more informed predictions, demonstrating the effectiveness of the approach in handling complex and heterogeneous data. This framework could be an important tool for clinicians seeking to predict disease outcomes and plan personalized treatment strategies.

From the paper [18]**Error! Reference source not found.** W. Lin et al. developed a 3D reversible Generative Adversarial Network (GAN) that facilitates bidirectional mapping between brain MRI and PET images. The aim of the paper is to improve Alzheimer’s disease diagnosis by combining the complementary strengths of MRI and PET imaging modalities. MRI provides detailed anatomical information, while PET reveals metabolic activity, and combining these two imaging techniques can lead to more accurate and comprehensive diagnoses. The methodology revolves around the use of a 3D reversible GAN that allows for the conversion of MRI images into PET images and vice versa. By enabling bidirectional mapping, the model can generate one imaging modality from another, effectively combining the unique advantages of both modalities. This technique offers a new way of utilizing multiple types of medical imaging data, potentially improving diagnostic outcomes. The results indicated that the 3D reversible GAN achieved high accuracy in diagnosing Alzheimer’s disease. By effectively merging information from MRI and PET images, the model provides a more robust and accurate diagnostic tool. This approach showcases the potential of using advanced GAN architectures to improve multimodal medical imaging and, ultimately, the diagnosis of complex diseases like Alzheimer’s.

From the paper [19] T. Chen, S. Kornblith, M. Norouzi, and G. E. Hinton presented a simple yet effective framework for contrastive learning aimed at improving the quality of visual representations learned by deep networks. Contrastive learning has become a popular approach in self-supervised learning, where models learn to distinguish between similar and dissimilar data points. This framework enhances the model's ability to learn more robust and generalizable features, which is particularly useful for downstream tasks such as image classification, object detection, and segmentation. In their methodology, the authors proposed a contrastive learning framework that uses pairs of similar and dissimilar examples to learn better visual representations. The model relies on a contrastive loss function to differentiate between positive (similar) and negative (dissimilar) pairs of data points. By optimizing this loss function, the model learns to map similar images closer together in the latent space, while pushing dissimilar images farther apart. This technique might lead to more meaningful and discriminative feature representations. The results demonstrated that the contrastive learning framework significantly improved the quality of visual representations, leading to better performance in downstream tasks. The simplicity of the framework, combined with its effectiveness, makes it a powerful tool for self-supervised learning, offering an alternative to traditional supervised methods that require large amounts of labeled data.

From the paper [20] K. He, X. Zhang, S. Ren, and J. Sun introduced the Residual Neural Network (ResNet), a revolutionary architecture in deep learning aimed at addressing the vanishing gradient problem, which often hinders the training of very deep neural networks. By incorporating residual connections, ResNet enables efficient training of extremely deep networks, facilitating the learning of complex representations in tasks such as image classification, object detection, and segmentation. This innovation allows the network to maintain performance as it grows deeper, a critical challenge in traditional architectures. In this methodology, the authors proposed a novel approach with residual learning using deep learning. Instead of learning direct mappings from input to output, the network learns residuals—the difference between the input and the desired output. This is achieved through shortcut connections that bypass one or more layers, effectively allowing gradients to pass through the network more easily during backpropagation. These residual blocks mitigate the vanishing gradient problem, enabling the training of much deeper networks without experiencing significant degradation in performance. The results showed that ResNet achieved remarkable success, winning the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2015. With a significantly lower error rate than previous models, ResNet set new benchmarks for image classification and object recognition tasks. The architecture's ability to scale to over 1000 layers while maintaining high performance demonstrated the power of residual learning, making it a foundational model in the field of deep learning. ResNet has since been widely adopted and has influenced many subsequent models and research efforts, solidifying its impact on the development of more complex and deeper neural networks.

III. COMPARITIVE STUDY

This paper presents a comparative analysis of two architectures of neural network models for the diagnosis of Alzheimer's disease: CNN+LSTM versus a 3D CNN-based approach with multichannel contrastive learning. Although both architectures are supposed to discover intricate patterns in Alzheimer's disease progression, their differences in architectures and dynamics of training lead them to different performances on accuracy, precision, recall, and F1-score.

Model Architectures and Training Behaviour: The CNN+LSTM model establishes the combination of Convolutional Neural Networks used for feature extraction and Long Short-Term Memory networks used to model sequential data. For more than 30 epochs, the training accuracy increases from 47.7% to 68.3%, which represents a reduction in training loss from 0.0102 to 0.0084. Validation accuracy varies between 52% and 62%, while validation loss reduces from 0.0105 to 0.0088. These oscillations may suggest overfitting, as the training accuracy increases while the validation remains static or drops and, notably, in epochs where validation loss spikes, like in epoch 20, where the validation accuracy dropped drastically to 40%. In contrast, the 3D CNN-based multichannel contrastive learning model described in the literature leverages multichannel MRI inputs and contrastive learning to improve classification. This architecture enables the model to capture spatial-temporal features more effectively, especially when diagnosing diseases like Alzheimer's, which affect brain structure over time. The reported validation accuracy for this model peaks between 75% and 80% across configurations, significantly higher than the CNN+LSTM model's performance. Additionally, the training curves for the 3D CNN architecture are more stable; in this case, consistent improvements in validation accuracy exist during each epoch, meaning the generalization to unseen data is better.

Performance Metrics Comparison:The CNN+LSTM model showed fluctuations in terms of classification metrics. The F1-score for classifying the stages of Alzheimer's was 76% for class 2 and 68% for class 3. With a sum of weighted accuracy of 62%, the weighted F1-score was 66%. While the model was surprisingly good in capturing particular classes, its macro-average precision was as low as 36% and macro-average recall at 31%. This suggests that the model had some difficulty working with the not-balanced case of Alzheimer's stages in the data set, given how the CNN component allowed for minimal feature extraction while the LSTM part was sub-optimally subjected to sequential learning.

In contrast, this paper presents a 3D CNN-based model which outperformed the CNN+LSTM model in most evaluation metrics. Due to multichannel inputs and incorporation of contrastive learning, this model managed to utilize data augmentation techniques better than the previous model, which used them for achieving more balanced classification accuracy and good control over Alzheimer's disease stages. The F1-scores, precision, and recall for the 3D CNN model turned out between 72% to 80% based on the applied data augmentation and hyperparameter tuning strategies.

Stability and Generalization:A key observation from this comparison is the difference in stability between the two models. The CNN+LSTM model, although improving in training accuracy over time, suffered from frequent validation accuracy drops and inconsistent loss reduction. These fluctuations could be indicative of overfitting, where the model learns the training data patterns too well but fails to generalize to unseen validation data. Deploying learning rate schedules or introducing dropout layers could also be used to make this model less prone to oscillations. Moreover, pre-trained models with better data augmentation techniques than standard rotation and flipping, including mixup, should help the model generalize across different stages of Alzheimer's.

However, the model 3D CNN-based performed better in generalization as it produced smoother loss curves and fewer fluctuations in validation accuracy. With the possible multichannel input processing capacity, this model could extract more comprehensive spatial-temporal features from brain images; contrastive learning even helped out with this model through focusing on learning such representations that would bring out the differences between healthy and Alzheimer's-affected brain regions, which led the model to boost up its classification performances.

IV. CONCLUSION

In comparison, this comparative study reveals that the 3D CNN-based multichannel contrastive learning model significantly outperforms the CNN+LSTM model in diagnosing Alzheimer's disease with validation accuracies ranging from 75% to 80% compared to the CNN+LSTM's maximum of 68.3%. The enhanced stability and generalization of the 3D CNN model are achieved because it uses multichannel MRI inputs along with a contrastive learning mechanism for effective capturing of relevant spatial-temporal features associated with Alzheimer's progression. Future enhancements to the CNN+LSTM can be incorporated by integrating contrastive learning techniques, employment of advanced data augmentation methods, and hybrid architectures that combine both spatial and sequential learning in order to enhance its performance and generalization capabilities.

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