ABSTRACT

Accurate brain tumor segmentation is crucial for diagnosis, treatment planning, and prognosis. Although magnetic resonance imaging (MRI) is a commonly utilized technique for brain tumorsegmentation, the heterogeneity of the tumor and the similarity of the surrounding healthy tissue can make the process difficult. This paper suggests a unique method for segmenting MRI brain tumors utilizing Long Short-Term Memory (LSTM) networks and Swin-Transformer (Swin-T) networks. On a range of image classification tasks, the hierarchical transformer-based vision model Swin-T achieves state-of-the-art performance. Sequential information is best captured by LSTM networks, which is advantageous for medical picture segmentation tasks that need spatial context. The suggested approach combines the long-range dependency learning of LSTM with the feature extraction capabilities of Swin-T. High-level features are extracted from MRI images by the Swin-T encoder, and segmentation masks are gradually improved by the LSTM decoder. The model incorporates a residual connection between the encoder and the decoder to improve accuracy by preserving spatial information that is lost during encoding. When tested on a benchmark dataset for brain tumor segmentation, the Swin-LSTM network performs better than previous methods. It generates robust and accurate segmentation masks, particularly for complicated tumors with irregular shapes. The efficacy of LSTM decoder, residual connection, and Swin-T encoder has been verified by ablation research. To sum up, this work provides a Swin-LSTM technique that uses LSTM for long- range dependency capture and Swin-T for feature extraction for MRI brain tumor segmentation. Its potential as a tool for clinical brain tumor diagnosis and treatment planning is enhanced by integration with a residual connection.

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LIST OF ABBREVIATIONS

ABBREVIATIONS		EXPANSION
CNN	-	**C**onvolutional **N**eural **N**etwork
AI	-	**A**rtificial **I**ntelligence
LSTM	-	Long Short Term Memory
SWIN	-	Shifted Windows
ACC	-	**A**ccuracy
MRI	-	Magnetic Resonance Imaging
RNN	-	Recurrent Neural Network
W-MSA	-	Window Multi-head Self Attention
SW-MSA	-	Shifted Window Multi-head Self Attention