# 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 tumor segmentation, 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**

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| **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** | **-** | ShiftedWindow Multi-head Self Attention |