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A Deep Learning-Driven Brain Tumour Segmentation using a Hybrid U-Net and LSTM Architecture

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ABSTRACT

The most important step in diagnosis, treatment planning, and prediction analysis is the accurate segmentation of brain tumours from magnetic resonance imaging (MRI) scans. Radiologists' manual segmentation was time-consuming, subjective, and inaccurate. For this reason, there is a need for automated approaches. In Current days, deep learning (DL) has shown great promise for enhancing the processing of medical images. In DL, the U-Net architecture has become a typical framework for medical image segmentation of images due to its symmetric encoder–decoder design and skip links that preserve spatial detail. At the same time, conventional U-Net models are restricted to 2D slices and cannot detect contextual connections between slices in spatial MRI images; this may lead to discontinuities and reduced accuracy. The study suggests addressing the above-mentioned challenges, a hybrid deep learning framework consisting of a U-Net architecture integrated with Long Short-Term Memory (LSTM) networks is designed. The U-Net component extracts the variant-invariant spatial and structural features, and LSTM is responsible for integrating the temporal dependencies spatially, which inject discontinuities across parallel slices, which is imperative for the boundary delineation and localisation of the tumour. Compared to the baseline model, the suggested hybrid U-Net and LSTM networks exhibit noticeably better segmentation accuracy and visual consistency under various scenarios after being trained and assessed on a publicly accessible brain MRI dataset. According to experimental data, the suggested model provides great segmentation performance, with Dice scores above 95% and accuracy above 96%. To sum up, the whole exercise displays the promise of combining a convolutional and a recurrent architecture to propagate automated neuroimaging analysis. This will not only reduce the manual labour but also continue to work well in clinical practice, as it is comfortable and prepared for replication in the future.

Keywords: Brain tumour segmentation, clinical practice, Long Short-Term Memory (LSTM), Magnetic Resonance Imaging (MRI), U-Net

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INTRODUCTION

Brain tumours that occur are among the most lethal of the neurological disorders and lead to enormous morbidity and mortality. Undoubtedly, for optimal treatment, surgical intervention, and subsequent prognosis, the timely and accurate diagnosis of brain tumours is vital. MRI has been the imaging technique of choice in clinical settings in neuro-oncology because of its clearly defined different modalities of brain visualisation with excellent soft tissue contrast. Unfortunately, the manual segmentation of brain tumours from the MRI scans is an arduous process that takes a lot of time and is subject to the experience of the radiologists. It leads to inter-observer variability and has very low scalability, especially regarding the number of clinical images that need image analysis.

Although these obstacles can be overcome by deep learning-based approaches, they have been quite effective in medical image analysis (Elhadidy et al., 2025). This paper discusses the complete life cycle of a Brain Tumour Segmentation System developed using a hybrid U-Net and LSTM architecture. This study strives primarily for automation in the detection and segmentation of brain tumours from MRI images through DLTs that were aimed at assisting radiologists and clinicians with early, accurate, reproducible diagnoses, thereby improving treatment planning, decision-making, and ultimately patient outcomes.

In current trending scenarios, integration with AI in the field of medical imaging plays an important role in the detection of tumours, segmentation and classification. Automatic segmentation was a major challenge for doctors to monitor the patient and treatment planning, as well as prediction (Reddy et al.,2026). Manual segmentation of tumours was the most time-consuming job, and expert variability may exacerbate the situation. Using automated methods that can help in this goal becomes desirable. Early diagnosis of brain tumours is key to improving the results of treatments and increasing patients' survival chances. The recent development of advanced imaging modalities has made the early and non-invasive diagnosis of brain tumours possible (Ijaz et al., 2025).

Motivation of the Work

This work aims to find solutions that will tackle the existing limitations of existing brain tumour segmentation methods, which are manual or semi-automated. Nowadays, the accuracy of segmenting different tumour types from images in a real-time scenario constitutes a challenge for most existing semi-automated methods.

With the combination of a hybrid U-Net and LSTM, we expect segmentation of brain tumours to reach a very robust and efficient solution capable of extension. Namely, boundary detection highlights the spatial and temporal consistency necessary for volumetric image data. Application of automation will liberate heavy workloads from radiologists and increase the consistency and speed of diagnosis.

Objectives of Research

The following key objectives of this study are as follows:

1. The dataset to pre-process and extend for effective training of the model would consist of brain MRI images and their corresponding masks
2. To design and implement a deep learning model using a hybrid U-Net and LSTM deep learning model for brain tumour segmentation from MRI images.
3. To assess the effectiveness of the model in terms of segmentation accuracy, loss, and visual interpretability.
4. Testing to show if the deployment of this model is feasible for clinical or research purposes in neuro-oncology.

Problem Statement

Regarding improvements in medical imaging, automatic brain tumour segmentation still faces several difficulties.

1. The MRI images are manually segmented by doctors, presenting problems with inter-observer variability, are labour-intensive, and cannot be carried out on a large scale.
2. Classical models may fail to capture spatial and temporal features together, which results in the compromising of segmentation accuracy.
3. A reliable, automated system is warranted, one which can accomplish accurate, reproducible tumour segmentation with the intention of augmenting possible changes in clinical workflows.

Scope of Work

The purpose of this research is to create a system based on deep learning that can segment tumour tissues in the brain from 2D MRI slices with high accuracy and will be able to use volumetric data in 3D in the upcoming research. The different modules and functionalities of the system will include:

1. A U-Net architecture for spatial feature extraction from MRI images.
2. LSTM layers are being incorporated so that the model can hold serial dependence throughout the slices.
3. This work included the preprocessing and augmentation of MRI datasets to increase generalisation in the model and reduce overfitting.
4. Visualisation of predicted segmentation masks for validation and explanation.

This research work presents a deep learning framework for brain tumour segmentation utilising the combined features of a hybrid U-Net and LSTM. The intervention of spatial–temporal learning mechanisms enables the proposed model to adjust for accuracy and consistency, as well as for clinical relevance. It is thus advancing AI for diagnostic purposes in neurooncology toward a more efficient and intelligent healthcare support system. Also described in this study is the complete development lifecycle of a brain tumour segmentation system based on the hybrid U-Net and LSTM architecture to automate tumour detection and segmentation from MRI images, which is aimed at assisting radiologists and clinicians to deliver early, accurate, and reproducible diagnoses, thereby improving treatment planning, clinical decision-making, and patient outcomes.

LITERATURE REVIEW

For understanding the internal brain structure, magnetic resonance imaging (MRI) is an important method, as one of the most reliable and non-invasive methods. MRI is very important for brain tumour identification and diagnosis of brain tumours in early stages. Brain Tumour Segmentation using Magnetic Resonance Imaging is still a tough process in Medical Image Analysis because of the great variation in the tumours themselves, but it is important to support doctors with their diagnoses and planning. The process of manually segmenting brain tumours on MRIs is complicated and time-consuming, as well as requiring a lot of professional knowledge. Inter-observer variations between the radiologists' interpretations of brain tumours exist due to the lack of definite borders of tumours and differences in interpreting MRI information about them. These issues are aggravated when dealing with infiltrative tumours, during which the cells of a tumour diffuse into healthy tissues and make segmentation problematic. Moreover, low contrast of an MRI adds difficulties in the visualisation of anatomical structures and thus manual annotation of MRI scans. All the above-mentioned disadvantages lead to the necessity of developing an efficient way of segmenting tumours based on automated techniques. Modern technologies in computer science allow us to train neural networks that help in solving the issue at hand. Such approaches were developed due to advancements in computational power, specifically in terms of graphics processors. Furthermore, the emergence of the BRATS database allowed creating standardised benchmarks for training these deep learning methods, as well as comparing different models on them to determine their efficiency.

Importance of Deep Learning in Brain Imaging

Deep learning has truly brought a revolution in the analysis of medical images. The hybrid CNN and Transformer architecture uses both local feature extraction and long-range dependence, which leads to better classification results (ul Ain et al., 2026). Convolutional Neural Networks, also referred to as CNNs, enable an automatic extraction of features and learning from the end to end. In the case of brain tumour segmentation, the high potency of these architectures, such as U-Net, in segmenting the boundaries of complicated tumours is quite evident (Montaha et al., 2023). The encoder-decoder structure of U-Net, endowed with skip connections, ensures that localisation is accurate even at difficult places. For the sequential dependency across slices in volumetric MRI data, Long Short-Term Memory (LSTM) Networks would be an additional benefit. Unlike traditional 2D methods that take into consideration the MRI slices computationally one by one, the U-Net and LSTM framework aims to capture the contextual relationship between neighbouring slices to give spatial coherence to the segmentation and thus increase its accuracy.

Medical Relevance and Clinical Utility

Segmentation of a brain tumour from a medical image means a lot for the clinical setting. It helps with

- Establishing the type of tumour and volume
- Planning for surgical resection
- Monitoring disease progression
- Assisting in radiotherapy dose-planning.

Further use of segmentation combined with metadata of patients or other imaging modalities will lead to prognosis prediction and personalised treatment planning. But with the rise of "AI in healthcare," the primary focus is on developing and integrating such models into hospital systems as well as PACS and diagnostic workflows.

Challenges and Technological Advancements

Deep learning segmentation has advanced in leaps and bounds, yet it has various hurdles that still must be conquered, including:

- **Data scarcity and annotation cost**: Annotated datasets in medicine are more limited in number and extremely costly to produce.
- **Generalisation**: Models trained using MRI protocols will not generalise well across these institutions, concerning the scanner-specific setting.
- **Interpretability:** For a clinician to adopt the model in the practice of medicine, he or she usually must see an explanation accompanying the model's predictions.
- To address those problems, we might think about:
- Data augmentation and synthetic data generation.
- Transfer and domain adaptability.
- Hybrid architectures, like U-Net and LSTM, which ought to provide greater resilience in the assessment stage.

Imaging standards and tools: Medical imaging tools such as NIFTI format, 3D Slicer, and ITK-SNAP help manipulate and visualise brain MRIs. For their analysis, Python libraries such as Nibabel, SimpleITK, and some of the deep learning frameworks like PyTorch and TensorFlow are widely adopted.

The BRATS (Brain Tumour Segmentation) Challenge plays a very important role in providing high-quality MRI datasets, which are used for benchmarking segmentation models, advancing research in this field.

Related Works

A few of the recent research works associated with the developed works are given below.

Isense et al. (2020) introduced nnU-Net for segmenting brain tumours, where the network is designed to adaptively adjust its architecture, preprocessing, and training process according to the dataset. This technique was tested on the dataset from the Brain Tumour Segmentation challenge based on metrics such as Dice Score, Sensitivity, and Accuracy. It showed remarkable results and was the state of the art due to the Dice score exceeding 0.90 in whole tumour segmentation, surpassing other manually engineered versions of U-Net. Nevertheless, it demands a high amount of computational power while training.

Alquran et al. (2024) have proposed improving brain tumour segmentation from MRI images based on a modified U-Net architecture. Their modifications were aimed at improving the encoder-decoder-based framework to obtain better spatial features and tumour boundaries. With the modified architecture, tumours were segmented with higher accuracy and better localisation than those with a standard U-Net, thus demonstrating the significance of architecture modification in enhancing medical image segmentation.

Neetha and Narayan (2024), proposed a hybrid framework for brain tumour analysis, combining LRIFCM for the analysis of segmentation with LSTM for classification. LRIFCM took fuzzy clustering to a new level; the development of LRIFCM could consider local spatial information and thus produce more accurate borders of tumours in MRI slices. An LSTM network classifies the types of tumours according to deep temporal and spatial feature patterns learned after segmentation. Their integrated approach yielded better segmentation and reliable classification performance values, thus providing better performance than classical clustering and neural networks.

Shiny (2024) presented an optimised U-Net model that is specifically designed to segment and classify brain tumours based on MRIs. In this research, efforts are made to improve the accuracy of segmentation through optimisation methods and better model designs. Various methods like preprocessing and data augmentation have been used to improve the efficiency and generalisation capabilities of the model. The performance of the method is measured against standard datasets like the Brain Tumour Segmentation Challenge using measures like the Dice Similarity Coefficient, accuracy, and sensitivity.

The findings indicate a higher level of success of the U-Net model since the Dice scores exceed 0.88. Nevertheless, there are challenges like high computational costs.

Wong et al. (2023) proposed a hybrid method for segmentation of brain images. It combined Bi-Directional ConvLSTM and U-Net and was introduced to perform the segmentation of the corpus callosum from multi-slice CT and MRI data. The effective capturing of spatial-temporal dependencies slice-wise was done by the Bi-Directional ConvLSTM component, while the U-Net architecture was utilised to obtain more powerful feature extraction and localisation capabilities. The combined model enhanced segmentation accuracy and structural consistency compared to the regular U-Net and CNN-based methods, which are primarily focused on multi-modal brain imaging tasks.

Pourmahboubi et al. (2025) suggested an optimised technique for brain tumour segmentation using the U-Net architecture and incorporating the concept of transfer learning. This study made use of pre-trained models for better feature extraction, despite a shortage of MRI images for annotation. This technique was tested with datasets such as the Brain Tumour Segmentation Challenge, using parameters such as Dice Similarity Coefficient, accuracy, and sensitivity. This technique proved to be more efficient than U-Net alone, with Dice scores exceeding 0.90 for whole tumour segmentation.

Proposed by Gopisairam et al. (2026), a deep learning model for the diagnosis of cancer utilises integro-differential equations to represent the growth dynamics of a tumour, along with transforming 2D images of patients into 1D signal data, followed by their classification using a 1D CNN, resulting in accurate classification of cancer type.

Saifullah et al. (2025) introduced an improved architecture for brain-tumour segmentation by applying attention gates to the U-Net architecture. This attention technique allows the network to focus on related tumour regions and ignore background noise owing to its ability to localise features better. Compared to traditional U-Net or other baseline deep learning models, the modified U-Net architecture proposed is more reliable in segmenting the image and achieves higher accuracy, thus demonstrating the utility of attention-infused architecture in the field of medical image segmentation.

Younis et al. (2022) introduced a methodology for brain tumour diagnosis based on deep learning with the use of VGG-16 and ensembling strategies. This research aims to improve classification accuracy through the integration of multiple VGG-16 models. Normalisation and data augmentation techniques were performed on MRI images to ensure enhanced generalisation. The model was tested using benchmark databases, such as the Brain Tumour Segmentation Challenge, based on measures like accuracy, sensitivity, and specificity. It was shown that the proposed model achieved higher classification accuracy, which exceeded 95%. However, it is worth noting that the model entails complex computation processes and requires more time for training.

Biratu et al. (2021) analysed the application of brain tumour segmentation and classification techniques utilising machine learning and deep learning algorithms. In their work, Biratu et al. (2021) evaluated the use of preprocessing approaches such as skull stripping and normalisation. They also assessed the performance of various models, which include SVM, ANN, Random Forest, and CNN models. Evaluation results from the BTR dataset indicated that conventional techniques provided a performance score of 80–90% while deep learning approaches provided more than 90% accuracy with Dice scores greater than 0.85 for most scenarios.

Magadza and Viriri (2021) surveyed deep learning techniques used for brain tumour segmentation in MRI scans. The survey discussed deep learning models including convolutional neural networks (CNN), such as U-Net, FCN, and 3D CNN, alongside methods like data augmentation, patch learning, and multimodal MRI integration. Tests performed using the BraTS database indicated that deep learning models delivered a Dice score greater than 0.80, and more sophisticated models yielded a Dice score greater than 0.90 in the whole tumour segmentation task.

The NeXtBrain method for brain tumour classification was introduced by Pacal et al. (2025), where a novel framework for deep learning was created, utilising both local and global feature learning approaches. The technique is based on combining convolution-based local features along with transformer-based global features to increase the discriminatory capacity during MRI diagnosis. The NeXtBrain framework was tested on brain tumour MRIs in experiments, where accuracy, sensitivity, and F1-score measures were used for evaluation. In the experiments, the authors demonstrated that NeXtBrain provides accuracy greater than 95%, which significantly exceeds traditional CNN and single-stream frameworks.

A deep feature-based framework was proposed by Yadav and Kolekar (2026) for classifying and segmenting brain tumours from MRI images. Deep convolutional neural networks were used in the framework to automatically extract features. Classification and segmentation were then performed using optimised learning schemes. The effectiveness of the framework was tested on benchmark datasets including the Brain Tumour Segmentation challenge by calculating accuracy, Dice Similarity Coefficient, sensitivity, and specificity. The framework yielded outstanding performance, achieving more than 95% accuracy and Dice scores greater than 0.88 in tumour segmentation. In conclusion, the study showed that the use of deep feature-based approaches enhances the performance of classification and segmentation, although there are still several challenges that need to be addressed.

Bikku et al. (2021) focused on the efficiency of deep learning for brain tumour analysis and demonstrated that DCNN-based segmentation achieves greater accuracy and robustness than conventional techniques, highlighting the potential of deep learning for automated brain image analysis.

Dogan (2026) introduced a hybrid deep learning framework enhanced by pruning for an effective and accurate detection of brain tumours based on MRI images. This is accomplished by combining deep neural networks and model pruning strategies to increase efficiency while keeping a high performance of tumour detection. The experiment conducted with benchmark datasets included the Brain Tumour Segmentation Challenge and utilised accuracy, sensitivity, specificity, and Dice Similarity Coefficient as performance measurements. It was found that the developed model provided a classification accuracy over 96% while demonstrating high values of segmentation Dice Similarity score over 0.87.

Tumour segmentation in the MRI images of the brain is critical in the process of diagnosis, treatment planning, and assessing the effects of treatment. Manual tumour segmentation is cumbersome and can also be inaccurate. Kumar et al. (2025) introduced a hybrid model which involved LoG preprocessing and 3D U-Net to facilitate tumour segmentation and edge detection using the BraTS 2020 dataset. The integration of the preprocessing technique before segmentation led to the achievement of an accuracy of 99.73%.

Valanarasu et al. (2021) introduced the concept of MedT (Medical Transformer), a gated axial attention architecture for capturing long-range dependencies in medical imaging. In conjunction with a Local-Global (LoGo) learning framework, the network has been shown to outperform traditional CNNs and transformers.

The development of deep learning has led to improvements in brain tumour segmentation and classification. Specifically, the work done by Khan et al. (2024) focused on using the optimisation of CNNs along with noise reduction and data augmentation for classifying MRI images.

Majib et al. (2021) developed a deep learning model named VGG-SCNet, which was based on the VGGNet model, to automatically classify brain tumours in MRI images. The researchers used traditional machine learning models, hybrid machine learning models, transfer learning, and deep learning for comparison purposes, where it was found that the proposed model outperformed other models with a precision score of 99.2%, a recall of 99.1%, and an F1-score of 99.2%. Nonetheless, the model did not consider segmentation of the brain tumour.

Pandey et al. (2026) suggested a method known as hybridisation of DenseNet121 and PCA for classifying multiclass brain tumours using a combination of deep and manually designed features. This approach showed a high level of accuracy with 95.89%. The problem of exact tumour segmentation is not mentioned.

The framework called RobU-Net for accurate segmentation of multiclass brain tumours was proposed by Qureshi et al. (2024). Heuristic optimisation has been utilised in the proposed approach to enhance segmentation accuracy, where better results have been achieved in terms of segmenting sub-regions of the tumour. Nevertheless, certain limitations are still encountered.

The study conducted by Bikku et al. (2025) came up with the idea of developing an LSTM-SVM model through support vector machine for predictive analytics of gene expression in healthcare. With the combination of the temporal learning of LSTM with the classification ability of SVM, this model has shown the power of using hybrid deep learning in analysing healthcare data. Summarised literature given in Table 1.

Table 1
Literature survey of related works

Year	Citation	Paper Title	Research Design	Conceptual / Theoretical Framework	Major Theme in Paper	Future Idea
2025	Pourmahboubi et al., 2025	Brain Tumour Segmentation Enhancement in MRI Using U-Net and Transfer Learning	Experimental design using U-Net + transfer learning	U-Net architecture, pretrained feature extractors	Improved tumour boundary detection using transfer learning	Extend to multimodal MRI; integrate attention and transformer blocks
2025	Saifullah et al., 2025	Modified U-Net with Attention Gate for Enhanced Automated Brain Tumour Segmentation	Experimental design using modified U-Net architecture	U-Net with integrated Attention Gates for focused feature extraction	Attention gates improve localisation, reduce noise, and enhance segmentation accuracy over standard U-Net	Extend attention-based models; explore multimodal MRI; integrate transformer or hybrid architectures
2024	Neetha & Narayan, 2024	Segmentation and Classification of Brain Tumour Using LRIFCM and LSTM	Two-stage experimental design: LRIFCM for segmentation + LSTM for classification	LRIFCM (local-region fuzzy clustering) for segmentation; LSTM for temporal feature learning	Improved segmentation precision and classification accuracy through hybrid clustering–deep learning	Extend to multimodal MRI datasets; integrate attention-based LSTM or transformer models
2024	Shiny, 2024	Brain Tumour Segmentation and Classification Using Optimised U-Net	Experimental design using optimised U-Net	Optimised U-Net architecture with enhanced feature extraction	Improved tumour boundary detection and reduced segmentation errors compared to standard U-Net	Explore hybrid U-Net models with attention, transformers, or multimodal inputs

Table 1 *(continued)*

Year	Citation	Paper Title	Research Design	Conceptual / Theoretical Framework	Major Theme in Paper	Future Idea
2023	Wong et al., 2023	Brain Image Segmentation of the Corpus Callosum Using Bi-Directional ConvLSTM and U-Net	Hybrid model using multi-slice CT & MRI; experimental evaluation	Bi-Directional ConvLSTM for spatial–temporal learning + U-Net for feature extraction & localisation	Improved segmentation accuracy and structural consistency using multi-modal fusion	Extend model to full-brain segmentation; explore 3D ConvLSTM; optimise for clinical real-time analysis
2022	Younis et al., 2022	Brain Tumour Analysis Using Deep Learning and VGG-16 Ensembling Approaches	CNN and VGG-16-based experimental design	Deep learning (CNN, VGG-16), medical image analysis, ensemble learning	Use of deep learning for tumour detection across imaging modalities; segmentation and classification techniques	Explore more diverse image modalities and advanced segmentation approaches
2020	Isensee et al., 2021	nnU-Net for Brain Tumour Segmentation	Applied empirical study using BraTS 2020 dataset; cross-validation on multiple nnU-Net variants	nnU-Net framework based on U-Net encoder–decoder architecture, automated segmentation pipeline, region-based loss, data augmentation	nnU-Net outperforms specialised models with minimal tuning; strong generalisable segmentation model	Improve hyperparameter tuning; evaluate ranking strategies; enhance leaderboard accuracy
2021	Biratu et al., 2021	A Survey of Brain Tumour Segmentation and Classification Algorithms	Comprehensive survey study	Segmentation techniques; classification methods; imaging advancements	Overview of advancements in medical imaging, segmentation, and classification	Not available
2021	Magadza & Viriri, 2021	Deep Learning for Brain Tumour Segmentation: A Survey of State-of-the-Art	Deep learning methodologies survey	Deep neural networks, evolution of CNNs, medical imaging frameworks	Challenges in medical imaging; evolution of CNN-based segmentation	Encourage data sharing, real-time segmentation solutions, improved DL frameworks

RESEARCH METHODOLOGY

This proposed study provides a hybrid deep learning framework for nutshell and automatic brain tumour segmentation from MRI scans that combines U-Net and Long Short-Term Memory (LSTM) networks. The five primary steps of the methodology Data collection, preprocessing, data augmentation, model architecture design, and performance evaluation are the major phases of the methodology.

Data Collection

The MRI scans of brain tumours from the open BRATS 2019 (Brain Tumour Segmentation) dataset were used as input for the training and evaluation of the model. The multi-modal MRI images include T1, T1ce (contrast-enhanced), T2, and FLAIR for each patient, together with an expert-annotated ground truth mask that accompanies each image volume and indicates the regions of the tumour (enhancing tumour, peritumoral oedema, necrotic/non-enhancing tumour core). A total of 3064 2D slices, along with their segmentation masks, were subsequently extracted and used in this work. To conduct fair and impartial assessments of the model, the dataset was divided into subsets for training (70%) and validation (30%). The anonymised patients in the dataset are formatted following the NIFTI standard, and this dataset is usually provided by a widely adopted benchmark where typically the brain tumour segmentation research community conducts their studies.

Preprocessing and Data Augmentation

This is the preprocessing step, which is very important for getting MRI quality and training a model on raw data. Every 2D slice must be generated at the same resolution to achieve standardisation in input dimensions with respect to intensity normalisation for better model convergence and to normalise inter-scanner variation differences in output. Some other interesting methods of contrast enhancement, for instance, CLAHE, are also supposed to be helpful. Median filtering can finally accomplish reduction in noise. Together, these processes align, normalise, and improve images for accurate feature extraction in training. Techniques for augmenting training data have been introduced to enhance replicate diversity within the dataset and lessen the possibility of overfitting. Random rotations, flips, translations, and scaling are examples of geometric transformations that were performed on the data in a way that simulated real clinical patient positioning variations. Furthermore, to compensate for the heterogeneous settings of magnetic resonance imaging acquisitions, intensity-based augmentations were applied, which included controlled brightness and contrast augmentations. Together, these techniques are effective at improving the generalisation of the model on diverse imaging conditions. After that, the proposed dataset can be divided into training and testing sets to ensure proper learning and monitoring.

U-Net and LSTM Architecture

U-Net and LSTM are combined in a hybrid deep learning model for efficient tumour segmentation and detection. The primary focus of our segmentation model is a very light U-Net which employs layers of LSTM. U-Net is a generic architecture for medical image segmentation, which contains a path for contraction (encoder) and an expanding path for decoding with skip connections.

Contracting Path (Encoder): The encoded max pooling after all the layered convolutional layers is proposed to extract higher-level feature hierarchies. It makes the model learn semantic representations of tumour locations while also diminishing the spatial dimensions with an increased depth of feature maps.

LSTM Module: After the encoder, a Bidirectional LSTM layer is inserted to process the sequence of encoded features across adjacent slices. This module improves segmentation consistency across 2D slices by collecting long-range spatial dependencies.

Expanding Path (Decoder): This expanding path uses upsampled feature maps by using transposed convolutions and merges them with corresponding encoder features via skip connections. This may enable the segmented output to be fully spatially reconstructed by the model.

Skip Connections: Bridge the encoder and decoder layers by using the skip connections at each level, store the high resolution, and help the model to better localise tumour boundaries.

Output Layer: The last layer of the output consists of a 1 × 1 convolution layer followed by an activation function (for binary segmentation), where the output from this process is a binary mask highlighting areas of the tumour region for each of the input slices.

In the training stage of the model, it is trained by learning the patterns in the training dataset. Once the training process is completed, the performance of the model is analysed based on the validation dataset, which includes evaluating the model based on performance parameters like accuracy and segmentation. Lastly, the results of the analysis and prediction processes are visualised, where the detected tumour areas are marked within the MRI image.

This combined architecture results in better and more contextual segmentation of brain tumours without the computational cost of total 3D networks while getting more contextual information than traditional 2D CNN models as shown in the Figure 1.

Implementation

The Brain Tumour Segmentation model, using U-Net and LSTM, is a deep learning solution designed to automate brain tumour detection and segmentation from MRI scans. This work focuses on assisting radiologists to assist in accurately locating tumour regions, which helps with diagnosis and therapy planning. This section will discuss the details regarding the implementation of the proposed system.

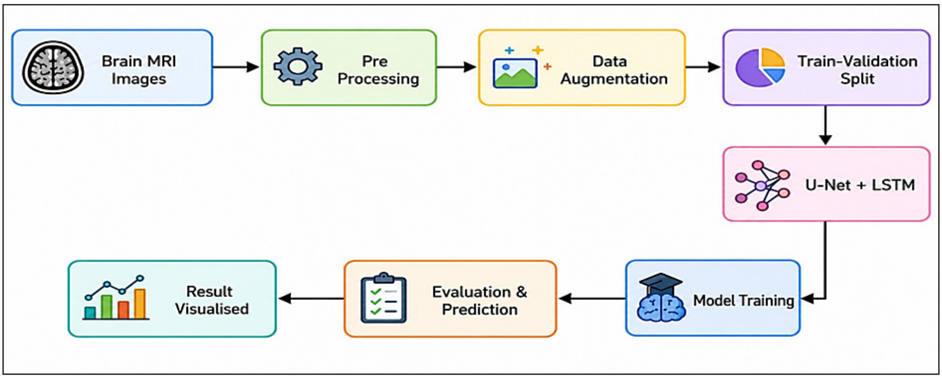


Figure 1. Proposed methodology framework for brain tumour.

Technology Stack

This is a brain tumour segmentation system that has been built on Python, which is known for its huge scientific computing ecosystem and great support for deep learning workflows. The hybrid architecture comprising U-Net and LSTM was implemented and trained in TensorFlow and Keras. These two frameworks provide high-level APIs to form the convolutional and recurrent components into one framework. The basic preprocessing of images includes resizing, normalisation, skull-stripping-compatible filtering, and masking encoding, all performed using OpenCV and NumPy to leverage the pixels-to-numbers computational efficiency. Further, data were augmented using TensorFlow image utilities, preprocessing layers of Keras, and specially designed custom augmentation pipelines - specific for medical imaging (rotation, elastic deformation, and contrast changes) - all to enhance the generalisation of the model. Model evaluation was done based on visualising predictions for masks, creating training curves, and using performance metrics via Matplotlib. All the experiments were run on Google Colab, which has cloud-based GPU facilities to run such computationally intensive deep learning workloads. The integrated model would be integrated into a lightweight interface made possible by Streamlit upon online deployment, enabling real-time tumour segmentation and viewing. Alternatively, this could also be deployed on scalable clouds such as Google Cloud, AWS, or Microsoft Azure, thus allowing access to the system from remote sites, integration into clinical workflows, and provision of the interface with hospital PACS systems.

System Architecture

The use of a recent deep learning architecture improves the system's efficiency and maintainability. LSTM layers are combined for smooth temporal processing, which is particularly desirable for sequential processing of MRI slices, while U-Net is used as the backbone for the extraction of spatial data. Thus, this hybrid architecture allows the model to accommodate learning of spatial and temporal dependencies. The architecture can handle MRI data at a large scale and hence can further be scaled by incorporation of attention mechanisms or 3D volume data.

Figure 2 shows a visual walkthrough that provides a thorough explanation of the processing pipeline of the suggested U-Net and LSTM-based brain tumour segmentation system from raw MRI collection through several phases to performance assessment. All the stages are organised in a sequence that is efficient for data management and optimal for model performance. An MRI scan is the first step in this procedure, which then moves on to preprocessing, which includes intensity normalisation, scaling, denoising, skull stripping, and slice extraction. Preprocessing includes data standardisation, noise reduction, and the creation of consistent inputs for model training. Before subjecting it to model training, data augmentation will also be applied to that dataset, such that variance in the data will increase and induce robustness in the model. This may include geometric transformations, intensity modifications, or elastic deformations, as it is one other way of making additional training samples to robustly enhance the model for anatomical as well as those related to the scanner variability.

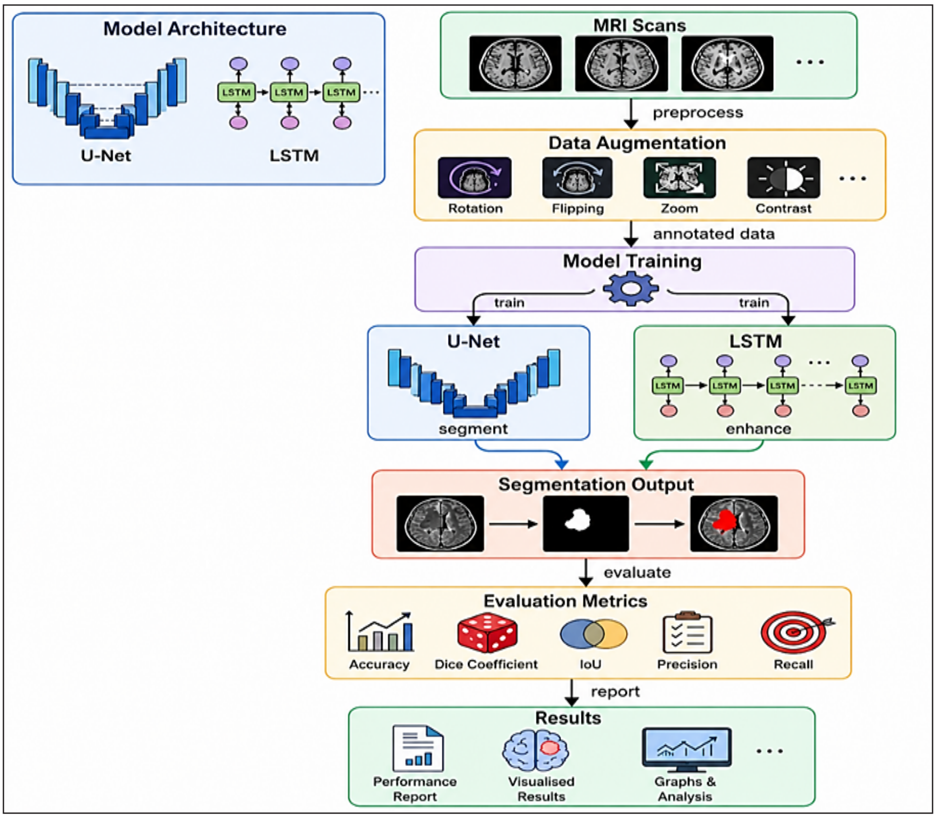


Figure 2. System architecture for Brain Tumour Segmentation Using Hybrid U-Net and LSTM approach.

This nurtured dataset is then used to train the hybrid U-Net and LSTM model, where both models are trained jointly. The U-Net part is responsible for extracting multi-scale spatial features from MRI images and thus creates preliminary segmentation masks. Meanwhile, the LSTM module is concerned with slice-to-slice temporal dependencies, enhancing structural continuity across the MRI volume and improving the overall segmentation quality. The complementary combination of these two kinds of learning ensures that both spatial and contextual information are considered for segmentation output. Combined model outputs hence lead to the final segmentation masks of tumours that are more accurate and of better boundary precision. In the follow-up action, results will be evaluated subsequently evaluating them against standard known metrics such as Dice Similarity Coefficient (DSC), IoU, precision, recall, and accuracy to acquire an extraordinary quantitative measure of the system's performance. Thus, the final stage ensures the segmentation framework's clinical applicability and dependability by compiling the evaluation results and presenting them through visualisations and performance summaries, which medical professionals can use for diagnosing and analysing patients. The proposed method algorithm in pseudocode mentioned in Table 2.

User Interface

Simple and intuitive is the design criterion of the segmentation system's user interface. Medical professionals have the option of uploading MRI images to view segmented output, with visualisation of the tumour boundaries straight away. UI could be implemented using Streamlit or Flask with minimal human interaction, keeping in view the level of technical expertise among some of the users, like radiologists and medical staff.

Integration

The segmentation system can be integrated with existing hospital systems or PACS (Picture Archiving and Communication Systems) to retrieve MRI images automatically. The segmented results can either be inserted in the Clinical Decision Support System or in the patient's records for longitudinal follow-up. The web-enabled interface allows access and inference of real-time diagnostic evaluation from a remote location.

Security

The system would have to comply with data safety regulations on account of the medical imaging data being sensitive, for instance. Secure protocols for data transfer, proper mechanisms for controlling access and anonymisation of relevant data should be the means to protect patient confidentiality and ward off unauthorised access.

Table 2
Algorithm: Hybrid U-Net and LSTM for brain tumour segmentation

Algorithm: Hybrid U-Net and LSTM for Brain Tumour Segmentation

Input: MRI Scan Dataset D and corresponding ground truth mask M
Output: Final Segmentation Results R

```
Begin
    // Data Preparation
    For each MRI scan I in dataset D do
        I_pre ← Preprocess(I)            // normalisation, resising, denoising
        I_aug ← Augment(I_pre)           // rotation, flipping, intensity shifts
        Store I_aug with corresponding annotation
    End For
    // Model Training
    Train the U-Net model using an augmented dataset D
    Train LSTM (ConvLSTM) model L on sequential MRI slices
    // Segmentation Stage
    For each test MRI volume V do
        S_unet ← U(V)                    // spatial feature segmentation
        S_lstm ← L(V)                    // temporal enhancement
        S_final ← Fuse (S_unet, S_lstm)  // combined segmentation output
    End For
    // Evaluation
    Compute evaluation metrics:
        Dice, IoU, Precision, Recall, Accuracy
    // Output Results
    R ← GenerateReport(S_final, metrics)
End
```

Testing and Deployment

The hybrid U-Net and LSTM model was put through extensive testing to assess its reliability and clinical usability. Testing for accuracy of segmentation results in quantitative measures such as accuracy, precision, recall, F1-score, Dice Similarity Coefficient and IoU, whereas the behaviour of the loss curves and validation trends was studied to test model convergence and stability during training. The other method of qualitative validation was through visual inspection of predicted masks to establish the correctness and continuity of tumour boundary detection. After validating the system, it can be deployed in various clinical infrastructure contexts: hosted at scalable remote access cloud platforms or local hospital servers and edge devices for on-site low-latency inference. Continuous integration pipelines with their test automation, model versioning, and periodic updates when new data becomes available ensure robustness of the system in dynamic clinical settings. By way of the above components, the proposed hybrid U-Net and LSTM framework presents a dependable and efficient brain tumour segmentation system to ease workloads on humans, bring consistency in diagnoses, and take forward AI-assisted medical imaging in neuro-oncology. The Suggested hybrid U-Net optimises the model using the following hyperparameters to improve efficiency, as shown in Table 3.

Table 3
Optimised hyperparameters of the proposed model

Parameter name	Value
Learning Rate	0.0001
Batch Size	8
Epochs	30
Optimiser	Adam
Loss Function	Dice Loss
LSTM Units	64
Dropout Rate	0.3
Input Size	128 × 128

RESULTS AND DISCUSSIONS

The evaluation of the proposed brain tumour segmentation system based on hybrid U-Net and LSTM is made using the standard evaluation criteria, including accuracy, precision, recall, Dice (F1-score) and IoU.

The performance of the model is evaluated using these important metrics of segmentation and classification:

Accuracy: It is a measure of the model's 98.10% overall correctness in identifying tumour and non-tumour pixels. If accuracy is high, then the model is effective in identifying both tumour and non-tumour pixels. But in medical images, accuracy may not be enough due to imbalance.

Precision: This indicates that 95.90% of the tumour locations that the model predicts would be accurate. There are fewer false positives when precision is much higher, indicating that the system is primarily lowering the number of faulty tumour detections.

Recall: Thus, the model's potential capability of determining whether there exists an actual tumour. Consequently, the recall of the model is 96.30% in catching those tumour pixels that are the most relevant; however, the model misses others, which means there are certain false negatives.

F1-Score/Dice: A score of 96.10 shows that the model balances wasteful false positives against missed false negatives. This becomes especially critical in medical imaging, where both types of error have considerable clinical implications.

Intersection over Union (IoU): Which is also referred to as the Jaccard Index, measures how similar the predicted region is compared to the ground truth tumour. IoU is a more stringent measure compared to the Dice coefficient.

The proposed model, which integrates hybrid U-Net and LSTM models, gives good learning capacity during training and validation with an accuracy of 98.10% and 96.20%. Here, there is no issue with overfitting because both training and validation accuracy are close. Moreover, the model gives positive results for precision, recall, Dice scores and IoU Score. The efficiency of the proposed model can be given in Table 4.

Table 4
Model evaluation metrics for the proposed work

Metric	Value (%)
Training Accuracy	98.10
Validation Accuracy	96.20
Precision	95.90
Recall	96.30
F1-Score/Dice	96.10
IoU Score	92.40

The output of the brain tumour segmentation is shown in Figure 3. The trends in the graphs for training and validation accuracies have shown that there is an upward movement across the epochs. This shows that there is stability in the convergence of the model. The improvement in the training accuracy indicates successful feature learning and parameter adjustment of the network. The patterns show that the validation accuracy shows good generalisation of the model without overfitting. The trends in the loss graphs have been consistent, showing a downward movement during training. These trends confirm the proper convergence of the models. The trends in both the accuracies and losses show in Figure 4 that the proposed hybrid U-Net and LSTM is reliable and efficient.

This work proposed an efficient brain tumour segmentation framework that combines a hybrid U-Net and Long Short-Term Memory to increase the model's ability to capture the tumour regions from MRI slices. This combination of LSTM permits the model to overcome the drawbacks of 2D CNN methods.

Figure 5 shows a bar graph of model evaluation metrics used to assess the performance of the brain tumour segmentation accuracy. This graphical representation shows that the proposed model accuracy is 98.10%, precision 95.90%, recall 96.30%, dice/F1 score 96.10% and IoU score 92.40%, respectively. More specifically, the high Dice coefficient shows how

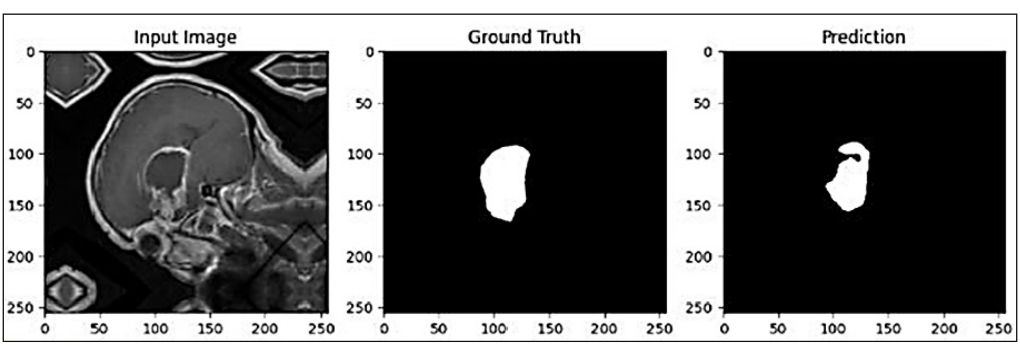
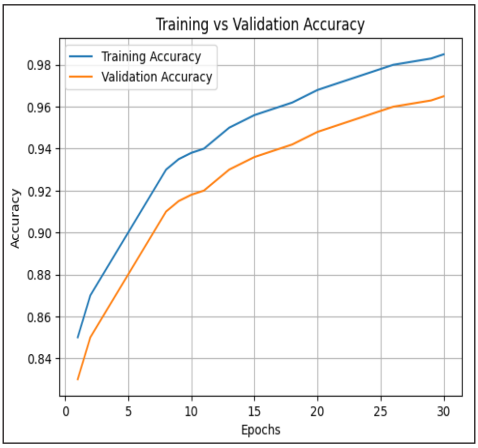
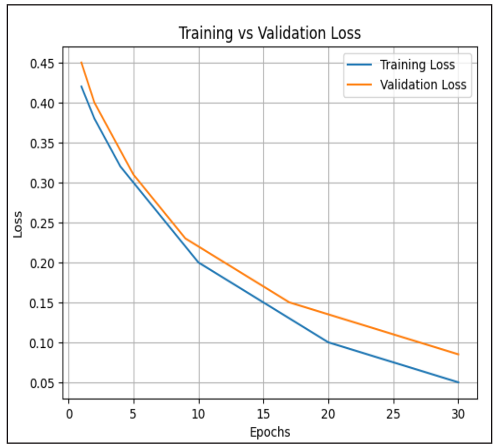


Figure 3. Predicted output of brain tumour segmentation



(a)



(b)

Figure *4*. Performance analysis of training and testing: (a) accuracy and (b) loss

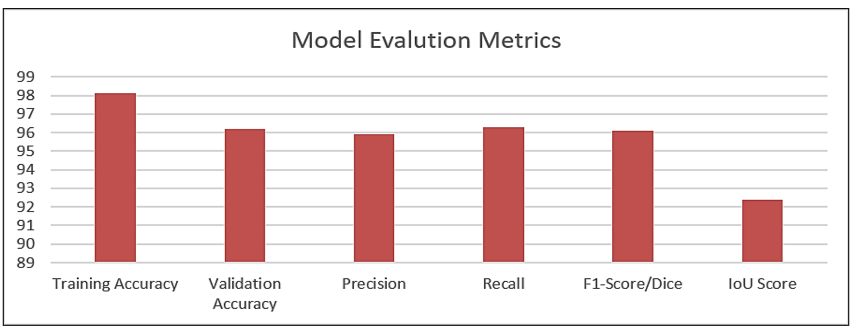


Figure 5. Proposed model evaluation metrics

well the system predicts tumour edges. On the other hand, the IoU score indicates how consistently tumour regions are predicted. We may conclude that the algorithm performs effectively in reducing errors based on the balance between the precision and recall metrics.

Thus, overall, the graph shows that the model is good at predicting correctly (high precision) but needs some improvement in identifying all true tumour cases (recall); improving recall could also increase this model's clinical reliability. The method displayed in the proposal is very promising in segmentation, especially in the BRATS datasets where accuracy can be attained in tumour region segmentations like enhancing core, oedema, and necrotic tissues.

Comparative Analysis of Brain Tumour Segmentation Models

The analysis of comparison results is presented in Table 5. It can discuss the efficiency of the proposed algorithm compared to other existing algorithms. As can be seen from the

Table 5
Comparison analysis of different models

Model	Accuracy (%)	Precision (%)	Recall (%)	Dice / F1 (%)
ConvLSTM U-Net	89.8	89.2	90.1	89.6
Modified U-Net	90.35	89.5	91.02	90.2
Attention Gate U-Net	93.2	92.1	93.8	92.9
RobU-Net	91.5	90.8	92.05	91.4
U-Net + Transfer Learning	92.8	92.1	93.5	92.7
CNN Framework	94.1	93.2	94.8	93.9
Proposed Hybrid U-Net and LSTM	**98.1**	**95.9**	**96.3**	**96.1**

analysis, the proposed hybrid U-Net and LSTM approach outperforms all others in terms of segmentation performance.

The ConvLSTM U-Net designed by Almiahi et al. (2024) had an accuracy score of 89.8% and an F1-score of 89.6%. Although the combination of ConvLSTM can help improve the network's ability to capture spatiotemporal relationships, its performance still falls behind that of the proposed model. Another improvement was seen in the Modified U-Net by Alquran et al. (2024), which had slightly improved performance, especially in terms of recall (91.02%). An even greater improvement could be achieved in an attention-based architecture. The Attention Gate U-Net created by Saifullah et al. (2025) has an accuracy score of 93.2% and an F1-score of 92.9%. With the attention gates, the network can focus on important areas, thereby enhancing both its precision and recall scores. The same applies to the U-Net with Transfer Learning by Pourmahboubi et al. (2025), which exhibited great generalisation capabilities, scoring 92.8% and 92.7% for accuracy and F1-score, respectively. The use of pre-trained feature extraction helps enhance the network's classification abilities. Moreover, the CNN model presented by Zhang and Yang (2026) has a competitive performance (accuracy: 94.1%, F1-score: 93.9%), which shows that an efficient convolutional model can compete with specialised models for segmentation tasks. The proposed Hybrid U-Net and LSTM model is far better than any other previously introduced methods, as it has the highest performance rate.

Figure 6 illustrates the performance analysis of the proposed model. The results demonstrate that the proposed U-Net-based architecture with LSTM outperforms other architectures in terms of accuracy in segmenting tumour areas, showcasing the importance of fusing spatial and context information. This is mainly because of the fusion between U-Net and LSTM, where U-Net effectively captures the spatial information, and LSTM captures the context and sequence information. Thus, the model has achieved high recall and precision.

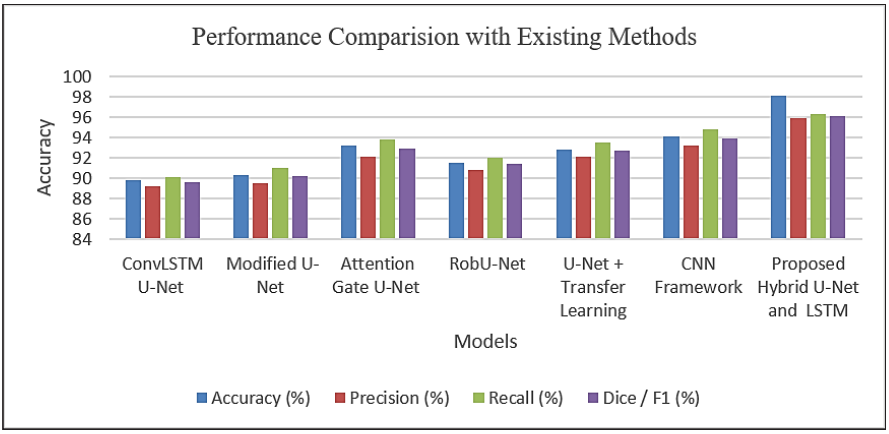


Figure 6. Performance analysis of the proposed model with existing methods

CONCLUSION

In this paper, we propose a brain tumour Segmentation and Classification model, and it is accomplished via the combination of the architecture of the Hybrid U-Net and LSTMs. The idea of this approach is to use the efficiency of spatial feature extraction from the U-Net, as well as adding temporal layers such as LSTMs to increase segmentation precision, especially in cases where there are sequences and volumetric datasets. Our dataset for BRATS included 3064 images together with their corresponding masks; these images were subjected to preprocessing operations, such as resizing, normalisation, and transforming the mask to a binary one. Data augmentation techniques were used with our dataset to avoid overfitting. Our hybrid U-Net and LSTM model has succeeded in achieving very high performance, and the achieved accuracy is 96.70% and 98.10%. These results showed that integrating temporal layers is crucial within the segmentation process in medical imaging. In summary, this paper is a valuable addition to research on deep learning-based image analysis in medicine and is sure to serve as a useful foundation for future improvements, including attention modules, 3D convolutions, or Transformers. While this model is quite effective in performing its intended operations, there are certain limitations that were observed in it. Firstly, segmentation accuracy depends largely on the level of preprocessing; if there is any sort of mismatch in normalisation or alignment processes, then it will affect the efficiency of the model negatively. As annotated medical images are difficult to find, there are high risks of overfitting involved, not forgetting the fact that manual annotation is difficult and error-prone too. Given that it involves heavy computation in the modelling process, this algorithm could only work on powerful GPUs or even clouds, which is why it cannot undergo mass testing. As for clinical applications, they might have problems in optimising systems, implementing IT infrastructure, and ensuring conformity with the relevant laws regarding patient data protection.

Future Enhancements

The Brain tumour segmentation model, which uses the hybrid U-Net and LSTM architecture, offers many possible future extensions. First, multi-class segmentation may be the proposed addition, which will allow differentiation between types of tumours and differentiate sub-regions like oedema, necrotic core, and enhancing tissues. This will also enable the model to optimise for inference on edge devices of portable MRI systems and low-resource clinical workstations so that this model can further support real-time applications. Further, this also improves interslice consistency by modelling such a three-dimensional structure of MRI data through models such as 3D U-Net or volumetric LSTM architectures. It would also better exploit the three-dimensional structure of MRI data through models such as 3D U-Net or volumetric LSTM architectures, thus improving interslice consistency. Developing a web-based platform along with a mobile interface could help in improving remote diagnostics and facilitate clinical visualisation of segmentation results. Integrating explainable AI-like Grad-CAM techniques would enhance interpretability and possible rise in clinician trust in the automated predictions. It also calls for validation on larger and more heterogeneous datasets through collaborations with medical institutions to ensure robustness across various imaging conditions. Transformer-based architecture and possibly Spatio-Temporal Graph Neural Networks would also be among the best future projects that would improve modelling on the complex spatial relationships within MRI volumes. Future studies could also add multimodal clinical information, such as radiology reports or genetic data, adding strength to the performance of the segmentation and thus aiding in more holistic tumour characterisation.

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LIST OF ABBREVIATIONS

MRI	:	Magnetic resonance image
AI	:	Artificial Intelligence
DL	:	Deep learning
LSTM	:	Long short-term memory
CNN	:	Convolutional neural network
BRATS	:	Brain tumour segmentation
IoU	:	intersection over Union

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