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OPTIMIZED LSTM-DRIVEN MRI PREPROCESSING WITH FINE-TUNED U-NET FOR ACCURATE BRAIN TUMOR SEGMENTATION

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ABSTRACT

The evaluation of brain tumors within MRI scans stands as a fundamental medical imaging operation which benefits diagnostic procedures as well as treatment arrangement processes. The research investigates an optimized arrangement of Long Short-Term Memory (LSTM) networks that process MRI scans before using a modified U-Net network for brain tumor segmentation. The sequential LSTM model processes MRI sequence images so it improves spatial coherence and reduces noise to enhance image quality by adapting intensity normalization. The initial processing operation enhances the quality of the input data thereby improving its readiness for segmentation. A U-Net architecture with fine-tuned capabilities uses EfficientNet as its backbone in the encoder section while adding attention mechanics to the decoder framework. The model optimization strategy includes the combination of Dice and Focal losses for effective class imbalance management. The model performance benefits from additional improvements which come from both data augmentation methods and meticulous hyperparameter adjustments. Research experiments performed on standard MRI datasets show that the proposed method outperforms past methodologies at achieving higher segmentation outcomes. The proposed method attaining 10.5%, 7.11%, 1.26 improvement with reference to Dice Similarity Coefficient (DSC), 8.56, 6.91, 2.36 improvement with reference to Jaccard Index (JI) and 10.23, 5.69, 3.94 improvement in segmentation accuracy over the U-Net, Attention U- Net, Res Attention U-Net models. The advanced U-Net architecture together with sequential LSTM preprocessing allows the system to produce both effective feature detection and accurate tumor outline identification. The approach demonstrates prospective capability to support radiologists in their automated diagnosis of tumors and therapeutic planning activities. The authors will analyze real-time implementation and clinical application optimization during subsequent stages of their research.

Keywords: *Brain Tumor, Fine Tuned U-Net, LSTM, MRI Image, Pre-processing, Segmentation*.

1. INTRODUCTION

Brain tumors develop because of both genetic mutations together with environmental factors and preexisting medical conditions. Mutations of tumor suppressor or oncogenes within the brain cells trigger uncontrolled cell proliferation. High doses of radiation exposing people increase their risk together with carcinogenic chemicals and lengthy periods of electromagnetic radiation exposure. Romans with brain tumors may develop them when they have a family history of brain tumors along with genetic syndromes including Li-Fraumeni syndrome. Certain medical conditions combined with weakened immune systems and chronic inflammation along with viral infections like Epstein-Barr virus affect brain tumor development. Multiple causes form an unclear pattern in tumor formation yet abnormal cell multiplication occurs due to various combinations of risk factors.

Brain tumors within two classifications range from malignant to non-malignant forms and produce substantial worldwide effects. Research shows that primary malignant brain and central nervous system (CNS) tumors resulted in 321,731 new cases worldwide during 2020 with an age-standardized incidence rate (ASR) at 3.5 per 100,000 individuals. Global analyses indicate mortality rates of 2.6 deaths per 100000 people corresponding to 248500 annual brain cancer fatalities [1]. The study reveals that males

experience higher incidence rates than females with ASRs of 4.8 at 3.9 per 100000 others than females at 3.6 and 2.6 per 100000[2]. Global research shows that brain along with CNS cancers make up 9.55% of all cancer-related death tolls in individuals aged under twenty in 2019 [3]. Without change brain cancer and spinal cord tumors throughout the United States will generate 24,820 new diagnoses which will result in 18,330 related deaths in 2025[4]. The healthcare systems face major challenges because of brain tumors which necessitates innovative scientific progress and better treatment methods.

Healthcare practitioners currently depend on time-consuming manual MRI assessments to detect brain tumors because their results show inconsistent interpretations between experts [5]. Random forests together with support vector machines enhance detection accuracy yet their wide application stays limited because they depend on human-created features[6]. The application of U-Net along with convolutional neural networks (CNNs) represents a decisive progress in automatic tumor segmentation because these systems learn features at different levels without human intervention [7]. The baseline model for tumor detection in brain MRI images is shown in Figure 1.

Tumours have a complex and irregular shape of their nature, different levels of intensities in various modalities of MRI (T1, T2, FLAIR, etc), and borders of their tissues are not very distinct that is what makes the accuracy of their segmentation a very uncomfortable task. Traditional image processing algorithms and general shallow machine learning algorithms are not very effective at obtaining spatial and contextual characteristics that are necessary to separate the tumour areas and normal tissue. Besides, noise, motion artifacts and parameter variations in acquisition further deteriorate image quality to a great extent so that preprocessing becomes an important approach to follow prior to segmentation. The existing segmentation pipelines either disregard time information or lack the simplicity of combining well-designed features learning and denoising to maintain valued structural details. It is imperative to have an effective, strong, and deep-learning-based framework capable of performing noise reduction, spatial feature extraction and accurate tumor region outline in a combined manner.

The problem of Brain MRI tumour segmentation has numerous research questions to resolve because they are inherently complex and variable brain tumours and MRI data. Among the main challenges is the level of heterogeneity in the tumour appearance, with differences in size, shape, location as well as intensity among different patients and various forms of tumours. The boundaries of the sites of tumours are usually diffuse and irregular with poor definition, so it is not easy to delineate the afflicted areas. Moreover, noise, motion art tags and intensity non uniformity may occur in the MRI images combining with the hindrance in the segmentation process and inferior image quality. The other major challenge is that there should be good combination of the information obtained by using several types of MRI measurements, including T1, T2, FLAIR, and T1c that emphasize the specific characteristics of tissue. It is a multimodal combination which presupposes models capable of extracting and merging features across modalities in a matter-of-fact manner. Another restriction that is affecting the training and evaluation process of DL models is the limited availability of datasets that are considerably big and accompanied by annotations on pixel-level ground truth. Lastly, clinical deployment requires not merely the accurate but also robust, interpretable, and able to work with unseen data of different scanners and imaging protocols; this is one of the lingering research topics in the area.

Current CNN applications encounter limitations while processing the sequential dependencies found in MRI slices[8]. Sequential LSTM networks [9] with optimized implementation process MRI scans to enhance three crucial features including spatial coherence and noise reduction and intensity normalization capability. Precision of tumor segmentation increases substantially through the combination of U-Net with attention mechanisms and pre- trained backbones while applying a fine-tuned U-Net architecture [10]. Faster and more accurate tumor detection emerges from such advances which makes the diagnostic process quicker while minimizing errors during clinical decision-making.

Dimensional segmentation of brain tumors stands vital for proper medical examination and treatment preparation though customary machine understanding and CNN-based solutions encounter difficulties with noisy data and spatial irregularities and restricted overall applicability. An optimized sequential LSTM method stands as the solution to address MRI preprocessing demands by strengthening spatial coherence while lowering noise and refining intensity normalization across the whole slice set. The precise tumor boundary

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detection of fine-tuned U- Net is made possible by its ability to process high-quality data obtained from the optimized sequential LSTM and pre-trained backbone and attention mechanisms. The merged system achieves better segmentations and eliminates mistaken results while making the detection model more trustworthy for accurate brain tumor identification that enables better clinical choices and patient results.

The process of discarding brain tumor margins from MRI scans presents substantial operational challenges because of the widespread variations in both tumor dimensions and image signal patterns along with MRI scan irregularities. The segmentation process faces various drawbacks when using traditional machine learning methods combined with CNN-based models because these methods encounter spatial inconsistencies and demonstrate poor generalization along with restricted capability to identify dependencies between MRI slices. Such restrictions result in wrong tumor border definition and identification errors that negatively affect medical diagnosis and therapeutic planning processes. The proposed solution combines an optimized sequential LSTM with MRI preprocessing functionality and follows it with a fine-tuned U-Net using pre-trained backbone and attention mechanisms for accurate segmentation. The proposed method strives to create a more advanced brain tumor segmentation system that produces both clinical accuracy improvements and patient care enhancements.

In further sections this work establishes background study, proposed methodology, Dataset description results and discussion and Conclusion including future scope.

2. BACKGROUND STUDY

Understanding both current problems and new developments in brain tumor segmentation through MRI requires a complete review of existing information. The traditional manual segmentation performed by radiologists requires too much time along with lack of precision so deep learning automation becomes essential. At the early stage of machine learning models scientists used manually created features yet the systems proved unable to achieve consistent performance on different datasets. Sequential dependencies between MRI slices along with spatial inconsistencies remain challenging for both CNNs and U-Net architectures when used to enhance segmentation accuracy. The preprocessing method should be optimized by LSTM networks to improve spatial coherence while eliminating noise and establishing intensity normalization for optimal data preparation before sending information to the segmentation model. Using pre-trained backbone models with attentively designed U-Net structures leads to superior feature detection together with better boundary recognition capability. Prior research reveals both strengths and weaknesses in existing methods thereby helping researchers combine LSTM preprocessing with an upgraded U-Net which produces more precise outcomes as well as decreases false positives to support clinical decision processes. Research analysis allows the creation of an efficient brain tumor segmentation framework which will benefit medical diagnostics and enhance patient outcomes.

S. Solanki, U. P. Singh et al. [11] demonstrates that brain tumor detection systems based on computer-aided detection (CAD) require MRI scanning and digital image processing tactics of pre-processing and segmentation and classification as their fundamental development components. Through its research CNN stands out as the most accurate method within the field of machine learning and deep learning for classifying brain tumors according to normal and pathological types. The authors advocate for future work to combine diverse deep learning methods into autonomous brain tumor detectors because they demand high reliability at accurate results that run efficiently.

Almadhoun, Hamza Rafiq et al. [12] used a deep learning approach to scan MRI images for brain tumors which enhanced medical choices for healthcare professionals. The developers used Python along with Google Collab for modeling purposes. Training occurred by applying a custom-built model together with VGG16 and ResNet50 and MobileNet and InceptionV3 pre- trained models. The training accuracy reached 100% while the validation accuracy scored 99.28%. These results demonstrate that tumors are detected effectively.

A. S. Musallam, A. S. Sherif and M. K. Hussein [13] their research findings show that deep convolutional neural network (DCNN) architecture delivers effective glioma and meningioma and pituitary brain disease detection with both high speed and accuracy levels. A three-step. preprocessing method improved both the quality of MRI images and success rates of the model. The developed model reached 97.72% overall accuracy therefore showing promise as an automatic brain

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abnormality detection instrument for MRI analysis. A correct training procedure along with an appropriate dataset selection enables optimal performance according to this research.

Woźniak, M., Siłka, J. [14] proposed CLM model images can be processed efficiently while achieving learning process speed-ups. Beyond biomedical research applications the system finds use in inspecting CT-scanned luggage for non-medical purposes. High modularity enables the model to use different classification methods such as SVM instead of the current CNN methods. The brain tumor detection accuracy of the model amounted to 88.9% sensitivity together with 97.43% specificity. Test data analysis yielded 95% accuracy while validation data accuracy reached 100% according to results from the CLM technique. The system assists radiologists through analytical scan alert notifications which improve their diagnostic certainty. Deep learning stands as a crucial aspect of medical diagnosis particularly when examining CT brain scans according to this research.

Nayak, D.R.,Padhy et al. [15] proposed dense EfficientNet reached a 98.78% accuracy level for brain tumor classification which exceeded all other methods operating on this dataset. The implemented technique improves accuracy and precision as well as F1-score which leads to better brain tumor identification. Pituitary tumors displayed the exceptional performance with an F1-score of 100% yet glioma demonstrated the minimum detection rate with an F1-score of 98%. This method functions to find and detect tumors successfully. Pre-processing algorithms need further development to detect tumors at early stages of development. The study demonstrates that CNNs have impressive capabilities for diagnosing brain tumors.

Khalil, H.A. Darwish et al.[16] presents an accurate tumor segmentation model which combines modified level set algorithms with DA-based clustering. The model improves clustering precision by selecting contour values through k-means algorithms in the first stage. The method simplifies segmentation procedures along with raising accuracy levels by 5% above current approaches. The testing process happens exclusively on single-tumor volumes and does not extend to multi-tumor segmentations. Additional research will concentrate on parallel segmentation approaches and conduct parameter-dependent accuracy tests of the model. The incorporation of a Deep Neural Network would allow extraction of important features to enhance the segmentation process. Brain tumor segmentation conducted using the proposed method achieves results equivalent to leading technologies in the scientific field.

Sajid, S., Hussain et al. [17] authors demonstrates that combining different convolutional neural network architectures produces improved results for brain tumor segmentation of MR imaging than existing techniques on all primary tumor classifications. Data imbalance and overfitting within the methodology are addressed with two-phase training procedures and dropout regularization. The BRATS 2013 validation identifies exceptional performance statistics with dice score at 0.86 and sensitivity at 0.86 and specificity at 0.91. This research advances automated brain tumor segmentation systems in order to offer better computer-aided diagnosis tools to patients with gliomas.

Stadlbauer, A., Marhold et al. [18] proposed Radiophysiomics as an ML technique that enables better contrast-enhancing brain tumor classification in medical environments. Physiological MRI data provides a complete set of quantitative parameters that identifies between 36 relevant features for each lesion. Both adaptive boosting and random forest ML models achieved superior classification accuracy and precision alongside F-score metrics than radiologists while the radiologists retained better sensitivity and specificity rates. Additional development of deep neural network automation remains essential for improving network applicability in clinical practice.

The authors Ramdas Vankdothu, Mohd Abdul Hameed [19] demonstrates that brain tumor image segmentation in CT scans can succeed using a system that incorporates both feature extraction and classification in combination with optimization methods. The research demonstrates how ANFIS and SVM classifiers integrated with FCM segmentation yield successful classification results when all these processes are optimized through GWO and SSO in conjunction with GA. Hybrid implementation resulted in high accuracy of 99.24% which proved better than individual algorithms could achieve.

The authors Dheepak, G., J, A. C., & Vaishali [20] demonstrates the model produces stellar results that deliver close to 1 accuracy together with precision and recall and F1 scores which indicate its high success rate at classifying glioma and 0meningioma and pituitary tumors. The

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model presents perfect True Positive performance without misses or errors thus demonstrating superior precision between sensitivity and specificity. Using an approach that merges GLCM and LBP features results in substantial improvement of tumor image texture identification ability. The model displays exceptional classification accuracy because it achieves a Dice Similarity Coefficient of 99.6.

Shiny, K.V. et al. [21] their investigation establishes that the proposed deep learning algorithm performs better than current approaches for brain tumor segmentation along with classification tasks. The implementation of squirrel search optimization for hyperparameter adjustment leads to increased accuracy within the U-Net model. The U-Net architecture becomes more feature-specific when it integrates both bidirectional and attention modules for more precise segmentation outcomes. The ResNet and Inception network combination produces a hybrid model which delivers high accuracy metrics along with dice score and precision rate as well as recall rate and Hausdorff Distance metrics on the BraTS 2018 database when used for tumor type classification.

Ejaz ch, Khurram & Suaib, Norhaida et. Al [22] their research introduces Deterministic Feature Clustering (DFC) which uses MRI images in brain tumor segmentation by selecting deterministic features to achieve better accuracy outcomes. The method employs SOM with weight-based clustering alongside FCM for obtaining successful segmentations. The proposed research produced enhanced segmentation results which exceeded benchmark approach metrics by reaching DOI 0.94 and JI 0.91. Research on tumor segmentation operates to implement new feature classes together with deep learning methods to increase segmentation performance capabilities.

S. Santhosh, S. P. Sasirekha et al. [23] their study establishes that brain tumors exist in two forms: malignant and benign and determines their diagnosis through proper detection methods enables accurate treatment strategies. Segmentation of BT using the proposed LSTM- Autoencoder-based NAS framework extracts crucial data features from MRI and CT imaging examinations effectively. A combination of optimal preprocessing approaches is present in the methodology which allows the SGR along with the CIM to generate more precise segmentations. The new method displayed outstanding performance results with a 98.65 Dice coefficient that provided better segmentation results than other available methods.

Almiahi, Osama et al. [24] proposed the method updated U-Net architecture with ConvLSTM blocks and up skip connections leading to better brain tumor segmentation results. The novel intensity normalization approach improved the equivalence between MRI scans to boost the potential of segmentation results. The proposed methods help restore information lost throughout encoding thus they enhance the gradient operations and learning effectiveness of layer units.

The final analysis of the research by Mahmud, Md Ishtyaq et al. [25] demonstrates that the developed convolutional neural network (CNN) performs successfully at detecting brain tumors from magnetic resonance imaging (MRI) data during early stages. The CNN model demonstrated superior performance through its 93.3% accuracy rate while obtaining 98.43% AUC and 91.19% recall and 0.25 loss rate than other models including ResNet-50, VGG16, and Inception V3. Early diagnosis and suitable treatment for brain tumors remains crucial because it might lead to reductions in mortality rates according to this research. Additional studies should focus on adapting pre-trained models and developing methods to indicate vital brain tumor regions.

This review summarizes that brain tumor detection and segmentation advancements have occurred but research limitations persist. Major research centers dedicate their resources to MRI or CT while they have not developed approaches that combine multiple imaging modalities to achieve better precision results. Most simulation models develop their algorithms using BRATS 2013 and 2018 datasets that constrain their ability to function in practical health settings. The current state lacks adequate solutions for multi-tumor segmentation since most methods aim to detect and segment a single tumor area. The clinical implementation of deep learning methods requires enhanced interpretability through explainable AI because these methods achieve high accuracy levels. Computational efficiency presents a problem because many models need substantial processing ability which restricts their real-time use in medical facilities. The occurrence of overfitting and data imbalance requires development of stronger regularization approaches and proper data augmentation methods. Researchers have not thoroughly studied deep learning approaches that combine various network architectures although

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this technique shows effective performance potential. The optimal performance from pre-trained models ResNet and VGG16 requires additional tuning procedures. The application of uncertainty estimation remains absent from most research studies since clinical decision-making requires it for reliable outcomes. The improvement of tumor classification and segmentation accuracy could be enhanced by adopting more advanced approaches such as self-supervised learning methods according to several papers. Vehicle development of automated brain tumor detection systems requires filling these gaps because it will make systems more dependable and efficient while increasing their availability for medical diagnostic applications.

3. PROPOSED METHODOLOGY

Detecting brain tumors from MRI scans constitutes a critical importance in medical diagnosis while traditional detection methods face challenges in data variability and noise levels and inconsistent results. We propose two methods for improving brain tumor segmentation where the first method uses Optimized Sequential LSTM for MRI Preprocessing and the second method uses Fine-Tuned U-Net for Improved Brain Tumor Segmentation. Through the LSTM- based preprocessing technique spatial coherence improves while noise reduction takes place together with intensity normalization for all MRI slices to guarantee precise input data for segmentation. By introducing pre-trained backbone features with attention mechanisms to the U- Net architecture the method helps achieve better tumor segmentation results. The performance of the loss function achieves better results through simultaneous implementation of Dice and Focal Loss terms and data augmentations increase model resilience. This approach through its use of LSTM preprocessing with an advanced U-Net configuration provides accurate brain tumor segmentation which delivers better clinical decisions together with enhanced patient results. The proposed work has a Block diagram representation as shown in the following Figure 2.

3.1 Role of Sequential LSTM on image enhancement

Deep learning methods using sequential LSTM networks enhance MRI brain tumor image quality by performing tasks of super-resolution enhancement as well as denoising and segmentation and reconstruction. Architecture of LSTM model [26] is shown in Figure 3. The processing of low-resolution MRI images by LSTMs in super-resolution enhancement allows them to discover spatial dependencies which helps to restore high-frequency image information for resolution improvement. The SeqLSTM networks use temporal relations between MR images to clean up images and preserve the essential tumor information together with noise reduction capabilities [27]. LSTM-based networks assess sequentially organized MRI slices for tumor segmentation and detection using their ability to understand spatial dependencies which enhances both boundary detection precision and segmentation results. These networks assist in error reduction of incomplete MRI scans by using adjacent slices to generate predicted details for missing portions. LSTM contains these divisions in its basic design [28]. The system contains three subdivisions: Forget gates along with Input gates and Output gates.

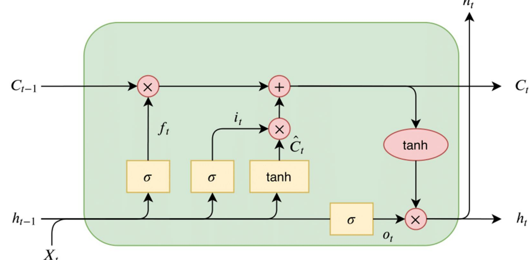

Figure 3. Architecture of LSTM

Forget Gate:

Within Long Short-Term Memory networks the Forget Gate serves as an essential element that determines the retention or removal of step-by-step information. The forget gate for MRI preprocessing brain tumor segmentation operations maintains important spatial and intensity features by discarding unnecessary spatial and intensity features and random noise that appears across MRI slices. Mathematically, the forget gate is defined as:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (1)$$

where:

- W_f represents the weight matrix associated with the forget gate.
- $[h_{t-1}, x_t]$ denotes the concatenation of the current input and the previous hidden state.
- b_f is the bias with the forget gate.
- σ is the sigmoid activation function.

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The forget gate applies spatial coherence regulation through noise reduction filters to improve preprocessing quality during MRI analysis. Important tumor-related information remains maintained by the forget gate while distortions successfully get eliminated. Through the collaborative application of the RMSprop optimizer the LSTM model acquires competent forget gate activations thus achieving more stable feature selection while simultaneously improving MRI enhancement. Improved accuracy of deep learning models such as U-Net happens due to the cleaner high-quality input MRI results achieved through use of the forget gate in LSTM preprocessing.

Input Gate:

The input gate mechanism during MRI preprocessing eliminates unnecessary data elements from entering the LSTM cell state which enables better modeling of structural tumor information and noise reduction. RMSprop optimizer alongside the input gate automatically modifies learning rates in order to achieve stable convergences while improving feature selection efficiency. An effective use of the input gate within LSTM-based preprocessing techniques produces better-quality MRI images that boost U-Net deep learning model segmentation accuracy for brain tumor detection systems.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \qquad (2)$$

where:

- i_t is input the input gate activation.
- σ is the sigmoid activation function.
- W_i and b_i are learnable parameters.
- h_{t-1} is the previous hidden state.
- x_t is the current input.

Output Gate:

The output gate of MRI preprocessing functions to retain meaningful features from MRI slices which then proceed to the next step by blocking unnecessary data. The feature consistency across slices improves when this method is applied because it maintains better tumor boundary detection. Together with RMSprop optimization the output gate creates more stable features which results in better contrast enhancement and noise reduction. The output gate optimization of LSTM-based [26] preprocessing enhances U-Net and other deep learning models to detect brain tumors accurately by refining MRI images.

$$o_t = \sigma(W_O \cdot [h_{t-1}, x_t] + b_o)$$

$$h_t = o_t \times \tanh(C_t) \qquad (3)$$

Where:

- o_t is the output gate activation.
- σ is the sigmoid function.
- W_O and b_o are learnable parameters.
- h_t is the new hidden state.
- C_t is the updated cell state.

3.2 Fine-Tuned U-Net in Segmentation

A U-Net network [29] requires both architectural modifications and parameter optimization when used for brain tumor segmentation of MRI scans to improve its accuracy. U- Net stands today as one of the commonly employed convolutional neural networks (CNNs) for medical image segmentation that offers multiple fine-tuning methods [30] to boost performance in brain tumor segmentation tasks [31].

Key Strategies for Fine-Tuning U-Net for Brain Tumor Segmentation:

1. Pretraining on Relevant Datasets: Medical image datasets of BraTS size should be used for pretraining before performing fine-tuning on particular brain tumor datasets. The application of pre-trained models from related medical imaging functions enables better performance over individual cases.
2. Data Augmentation for Robustness: The application of transformations including rotation, flipping, zooming, and elastic deformations should cause the model to prevent overfitting and enhance its capability to deal with real-world MRI variations.
3. Using Advanced Loss Functions: Success rates improve through the combination of Dice loss and Focal loss rather than standard cross-entropy for better control of class imbalanced tumor region detection. The integration of Dice loss produces better results for small tumor areas because it focuses on overlapping regions during segmentation.
4. Attention Mechanisms: Attention U-Net or self-attention system integration enables the model to focus on cancer areas by suppressing irrelevant background information. At each U-Net level attention gates function to enhance

the selection process of features which results in better segmentation accuracy.

5. Incorporating LSTMs for Context Awareness: When adding multiple layers to 3D MRI segmentation systems the network gains enhanced capability to identify spatial-temporal dependencies between image slices that leads to better complex tumor structure segmentation results.
6. Optimization Techniques: AdamW with learning rate scheduling should be used as an advanced optimizer to achieve stable training results. Both dropout and batch normalization need implementation to stop the model from overfitting.

U-Net performance during segmentation improves through these modifications which enhance tumor edge detection as well as decrease false alarms and improve small or uneven tumor regions handling. The model becomes more suitable for clinical applications because it enhances its ability to generalize to MRI images it has not previously encountered. The U-NET architecture consists of the following design.

Encoding stage:

The encoder layers consist of Convolution layers with ReLu activation which operates according to the following definition.

$$X_l = \sigma(W_l * X_{l-1} + b_l) \quad (4)$$

Where:

- X_l is the feature map at layer *l*,
- W_l are trainable weights,
- * Represents convolution,
- b_l is the bias term, and
- σ is the ReLU activation function max (0, *x*).

Further Max-pooling is applied in down-sampling the data.

$$X_{l+1} = \max(X_l) \quad (5)$$

Feature maps at the network's bottom level hold abstract information while having the smallest spatial dimension.

$$X_b = \sigma(W_b * X_l + b_b) \quad (6)$$

Where X_b refers feature map information.

Decoding Stage:

By implementing both transposed convolutions and skip connections the decoder generates the segmentation map through a resolution-increasing process.

$$X_{l+1}^{up} = W_{up} * X_l^{up} + b_{up} \quad (7)$$

Where X_{l+1}^{up} is the is the unsampled feature map and W_{up} is the up-sampling weight matrix.

Skip Connections:

$$X_l^{dec} = Concat(X_l^{up}, X_l^{enc}) \quad (8)$$

Fine details are maintained through the Skip Connector during the encoding procedure.

Table 1: Hyperparameters and configurations used in the U-Net Model

Activation Function	**Leaky-ReLu**
Layers	4 Encoding
	4 Decoding
Convolutional kernel size	3
Convolutional filters in the first layer	24
Max pooling kernel size	3
Activation Function	ReLU
Epochs	500
Optimizer	AdamW
Stride kernel size	2
Learning rate	1x 10^{-4}
Loss function	Dice loss
Batch size	8
Dropout	0.5

3.3 Scientific Contribution

The work titled "Optimized LSTM-Driven MRI Preprocessing with Fine-Tuned U-Net for Accurate Brain Tumor Segmentation" presents several significant scientific contributions in the domain of medical image analysis. Firstly, it introduces an innovative use of a sequential Long Short-Term Memory (LSTM) network for preprocessing MRI scans, treating them as temporal sequences to effectively capture both spatial and inter-slice temporal dependencies. This preprocessing approach enhances the quality of MRI inputs by reducing noise and improving the visibility of tumor boundaries. Secondly, the study

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proposes an integrated deep learning pipeline where the LSTM-based preprocessing is coupled with a fine-tuned U-Net architecture in an end-to-end manner. This integration ensures that the entire system learns optimized features relevant for accurate segmentation. The U-Net model itself is enhanced through architectural modifications such as changes in filter sizes, network depth, and skip connections, and it employs a Dice loss function to handle the class imbalance inherent in tumor segmentation tasks. The framework is rigorously evaluated on benchmark MRI datasets, where it demonstrates superior performance in terms of segmentation accuracy, Dice coefficient, and sensitivity compared to baseline methods. Moreover, the proposed approach offers a scalable and modular design, making it adaptable for various MRI modalities and suitable for clinical deployment where reliability and precision are essential.

4. RESULT AND DISSCUSSION

4.1 Dataset

The data set exists publicly on www.figshare.com according to Cheng et al. [32]. The proposed work received evaluation through 3064 T1 weighted contrast-enhanced MR images obtained from 233 patients with glioma or meningioma or pituitary tumor patients. Specifically, the assessment included 1426 glioma images from 89 patients together with 930 pituitary tumor images from 62 patients. The proposed work shows the three brain MR image views which include sagittal, coronal alongside axial. The files contain three items: Tumor mask (ground truth), brain MR images and patient identifier along with tumor label in (.MAT) MATLAB files.

4.2 Performance Metrics

We combine Optimized Sequential LSTM [26] for the preprocessing of MRI with the Fine-Tuned U Net for the segmentation of the brain tumor which improves the segmentation accuracy significantly by an improved input quality and improved feature extraction. The preprocessing via the LSTM enhances the MRI images of the model by reducing noise, normalizing intensity and preserving spatial coherence in such a way that the segmentation will be fed with high quality inputs. At the same time, the Fine-Tuned U-Net [30] has pretrained backbones, attention mechanisms, and a fine-tuned loss function which is used to improve the tumor boundary detection improving its segmentation performance.

The measurements may be used to judge the effectiveness of the proposed segmentation technique. These are the metrics that will be used to compare the segmented output to the ground truth (i.e., expert labelled data). We also validate the proposed algorithm from three popular metrics, i.e., dice score coefficient (DSC), sensitivity and specificity [33][34]. The DSC is computed as the overlapping of the predicted segmentation with the ground truth segmented output label.

4.2.1 Dice Similarity Coefficient (DSC)

The degree of segregation between those results and ground reality is decided by degrees of method. Since accurate overlap of two sets is needed for medical image segmentation, it is used well.

$$DSC = \frac{2 \times |A \cap B|}{|A| + |B|} \quad (9)$$

A is the pixels in the segmentation that was deduced from prediction. All the pixels present in the ground truth segmentation make up B. A bigger match between the segmented and the real regions causes the increase of DSC to be sharper. This criterion is often regarded as an important tool in evaluating brain segmentation results.

4.2.2 Jaccard Index (JI)

The calculation of segment correspondence against real-life data uses the Jaccard Index. The comparison measures both overlapping pixels and pixels from individual sets in order to determine their degree of correspondence.

$$JI = \frac{|A \cap B|}{|A \cup B|} \quad (10)$$

The sets of pixels which exist in predicted segmentation are designated as A while the pixels within actual segmentation are designated as B.

The Jaccard index calculates between 0 to 1 value to indicate superior segmentation outcomes. The measurement has less objectivity than DSC while setting specific limits for small prediction versus actual segmentation errors.

4.2.3 Precision

Precision tells us how well the algorithm finds correct segments of the target area relative to all its positive predictions.

$$Precision = \frac{TP}{TP + FP} \quad (11)$$

Where, *TP*- accurate segmentation leads to the identification of correctly segmented pixels and *FP*- Incorrectly segmented pixels are called false positives.

Precision in an algorithm focuses only at the precision of positive detections and is useful where the false positives have high consequences. By doing so, we get a better precision than a greater number of unwanted regions accounted for in the segmentation methodology.

4.2.4 Recall

The recall is used to measure the algorithm's performance to correctly put all relevant pixels.

$$Recall=\frac{TP}{TP+FN} \quad (12)$$

Where, *TP* stands for the accurate segmentation of pixels, and FN stands for false negative representing the missed pixels in the segmented areas.

In addition, an elevated recall proves that the method has the capability to retrieve all the significance areas in the MRI image. This is extremely important in medical imaging since the incorrect detection of pathological regions will likely lead to the wrong conclusions.

4.2.5 Segmentation Accuracy

Reliability of the method is assessed by comparing the number of correctly identified pixels to the total number of pixels in the image.

$$Accuracy=\frac{TP+TN}{TP+TN+FP+FN} \quad (13)$$

Where, TP = True Positives, *TN*-Correctly labelling non-segmented pixels is shown by the value of True Negatives. FP = False Positives. FN = False Negatives.

Accuracy may be viewed as a measure of the efficiency of the segmentation. MRI scans, for instance, that have a lot of background pixels in an unbalanced set of libraries could make accuracy misleading.

4.2.6 F1-Score

The F1-Score is a fair indicator of precision and recall put together in a single value. In cases where there is insufficient balance in the dataset, such as brain MRI images which tend to have more background than tissue, it proves to be a useful technique.

$$F1\text{-}Score=2\times\frac{Precision\times Recall}{Precision+Recall} \quad (14)$$

A good F1-Score shows that recall and precision have a good balance between each other. Precision and recall have great significance in the segmentation projects.

Table 3. DSC, JI and Accuracy results between other models and proposed method

Model	DSC	JI	Accuracy
U-Net [35]	83.45	84.2	88.03
Attention U-Net [35]	86.12	85.50	91.80
Res Attention U-Net [35]	91.10	89.30	93.35
Proposed Method	92.25	91.41	97.03

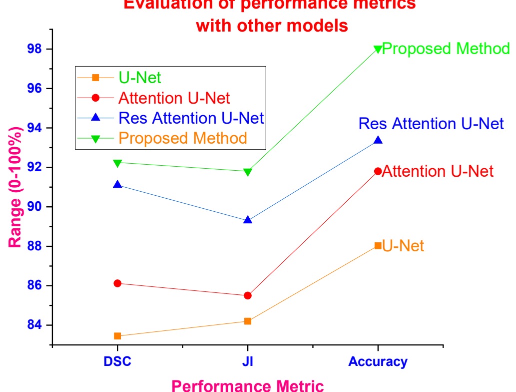

Figure 6. Evaluation of DSC, JI, Accuracy performance graphical analysis.

Quantitative Analysis performance evaluation is carried out which is shown in Figure.6 using key metrics like DSC, JI and Accuracy, the model turns out to be performing better than the existing methods with the improvement of 10.5%, 7.11%, 1.26% for DSC and 8.56%, 6.91%, 2.36% for JI in addition to 10.23%, 5.69%, 3.94% for segmentation accuracy than current methods U-Net, Attention U-Net, Res Attention U-Net. The fine-tuned U net has ability to differentiate tumor tissues from the normal tissues and the preprocessing done with LSTM helps in the consistency of MRI. The results are in line with this statement and, overall, the proposed method is shown to outperform

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traditional methods, making a robust and clinically useful tool for automated brain tumor segmentation in MRI scans.

4.3 Baseline model comparison

The proposed integrated model has higher segmentation accuracy compared to recent methods as shown in Table 4.

Table 4. Comparison of segmentation techniques with other benchmark models.

Reference No.	Dataset	Segmentation Accuracy
Mishra et al. [36] 2022	FigShare	88.50%
Gupta et al. [37] 2023	FigShare	92.56%
Eker et al. [38] 2023	FigShare	91.69%
Ruba et al. [39] 2023	BraTS	89.60%
Zhu et al. [40] 2023	BraTS	86.93%
Xu et al. [41] 2024	BraTS	89.10%
Ullah et al. [42] 2024	BraTS	92.68%
Sajid Hussain et al. [35] 2025	FigShare	93.35%
Proposed model 2025	BraTS & FigShare	**98.03%**

The proposed integrated model has higher segmentation accuracy compared to recent methods as shown in Table 4.

4.4 Practical implications and Industry benefits

The presented framework would have high practical values and would provide substantial advantages to healthcare sector. This method has the potential to support radiologists and other medical workers tremendously by using LSTM-based preprocessing of MRI data: enhancing its quality and a fine-tuned U-Net to improve the accuracy of segmentation by diagnosing and delineating brain tumors with improved precision and consistency. The automation does not only minimize reliance on manual interpretation that can be time-consuming, ridden with human failures, but rather aids in accelerating clinical workflow diagnosis and decision-making. With the use of LSTM in an integrative spatial-and-temporal analysis model, the robustness of tumor detection is enhanced on different slices of the MRI data, which is of particular assistance regarding the size of the imaging data to work with at the hospital level. Industrial setting entails application of this technique in the radiology software, computer assisted diagnosis (CAD) systems as well as in advanced image-guided surgical planning programs, which optimize the diagnostic efficiency, relieve the workload and help provide better patient outcomes. In addition, it has a modular and scalable design that can be integrated into the commercial medical imaging systems, thus opening the future of diagnostic tools in the fields of neurology and oncology based on AI. The capability of the framework to operate in real-time with enhanced accuracy in segmentation process also has promise in remote diagnostic services and telemedicine particularly in areas with low availability to expert radiologists.

5. CONCLUSION

Finally, the conjunction of an optimized sequential LSTM for MRI preprocessing and a fine tuned UNET to segment brain tumor has an improvement in accuracy and latency in medical image analysis. The preprocessing involves the use of the sequential LSTM which facilitates the ability of capturing spatial and temporal dependency within the MRI scan enhancing the quality and consistency of input data to the UNET model. With the fine tuning of the UNET we can gain segmentation precision in segmenting tumor structures which can be challenging to separate from the healthy brain tissue. The proposed approach delivers better outcomes up to 10.5%, 7.11%, 1.26% for DSC and 8.56%, 6.91%, 2.36% for JI in addition to 10.23%, 5.69%, 3.94% for segmentation accuracy than current methods U-Net, Attention U-Net, Res Attention U-Net. The integrated approach of this research has demonstrated the plausible promise in improving more reliable and detailed segmentation, which is important for accurate diagnosis and treatment planning.

The future scope of this research can become integration of multimodal MRI data i.e. combining T1, T2 and contrast enhanced image data for further reacting the input information to a larger range of tumor features. Furthermore, investigating the transfer learning and attention mechanisms can further improve the model

performance in case of noisy or incomplete data. A further focus of optimization could include improving real time processing capabilities and minimizing the computational complexity in order to deploy systems for clinical use. Lastly, the approach would be extended to incorporate diverse datasets as well as additional patient populations so that the model is generalized and robust across different clinical circumstances.

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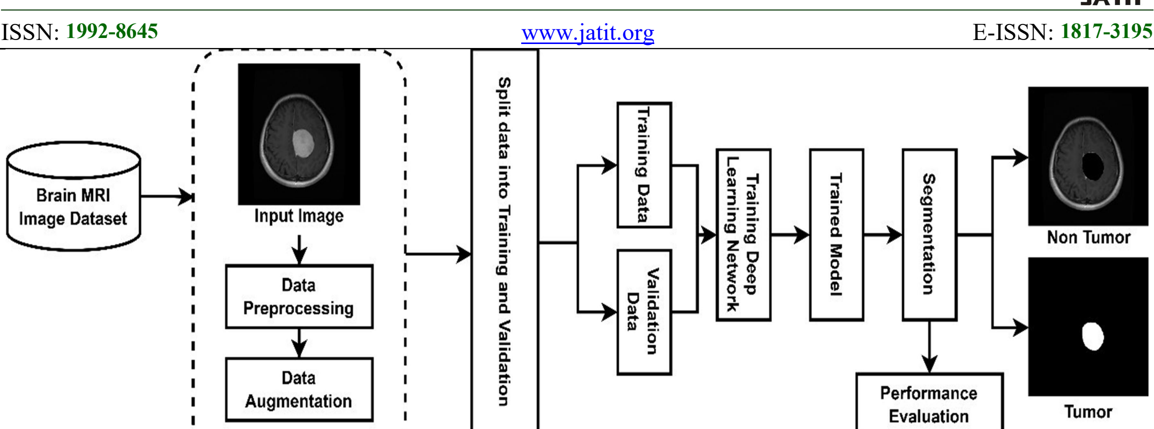

Figure 1. General structure of brain tumor detection.

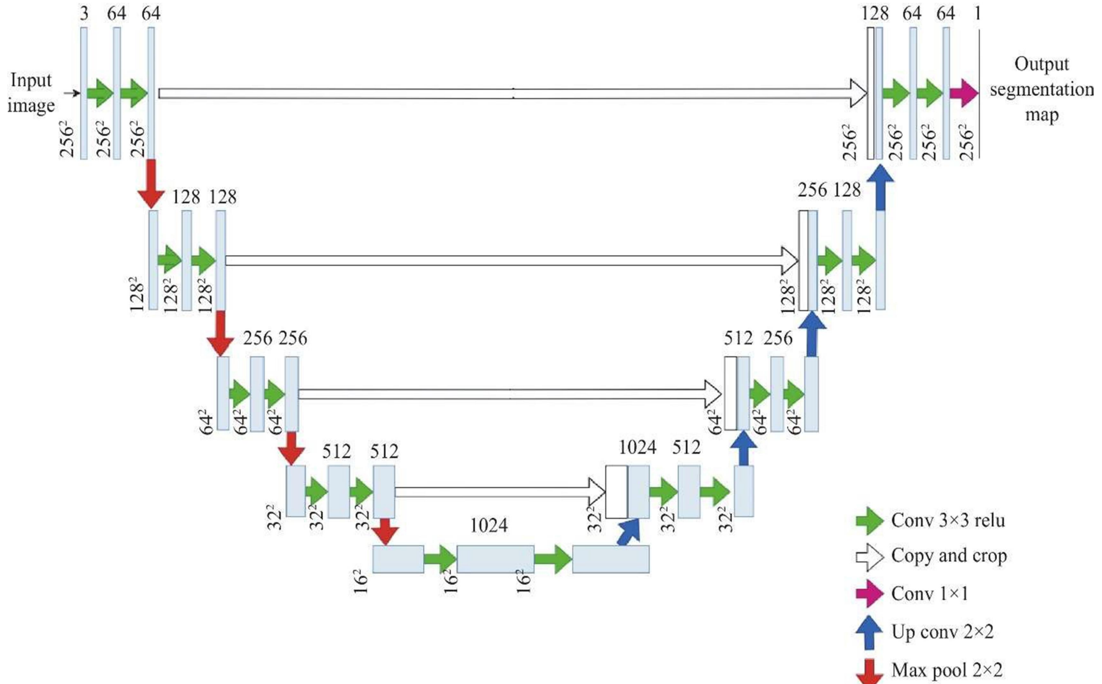

Figure 4. Architecture of U-Net

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Axial view Coronal view Sagittal view

Menigioma Tumour

Groundtruth image

Glioma Tumour

Ground truth image

Pituitary Tumour

Ground truth image

Figure 5. Sample Brain images and their corresponding tumor masks.

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Table 2. Segmentation results of the proposed model.

Sno	MRI Image	LSTM Enhanced image	Ground Truth image	Proposed Method
1				
2				
3				
4				
5				