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Unified CAD Framework For Brain Tumor Prediction And Segmentation Using Hybrid CNN-LSTM And 3D U-Net Architectures

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***Abstract*—*Brain tumors are among the most aggressive and life-threatening malignancies, requiring accurate detection and segmentation for effective treatment planning. Deep learning has significantly advanced medical imaging, but most studies focus on either tumor classification or segmentation, limiting their clinical utility. This paper extends our previous research on CNN-LSTM-based cancer prediction and U-Net-based glioma segmentation into a unified computer-aided diagnosis (CAD) framework. The proposed system first employs a 3D U-Net to localize tumor subregions from multi-modal MRI scans (BraTS 2020 dataset), generating voxel-wise masks for necrotic/non-enhancing core, peritumoral edema, and enhancing tumor regions. These segmented regions are then processed through a feature fusion strategy, where automatically extracted CNN features are combined with handcrafted features and classified using an LSTM-based network to predict tumor grade. Experimental evaluation demonstrates superior performance with a Dice score of 78%, mean IoU of 90%, and classification accuracy of 99.2%, surpassing existing standalone models. The integration of segmentation and classification reduces false positives, enhances interpretability, and provides a clinically relevant diagnostic tool. This study highlights the potential of end-to-end hybrid CAD systems in neuro-oncology and outlines pathways for incorporating explainable AI in future work.*

Keywords*—*Brain Tumor, CAD, Deep Learning, 3D U-Net, Feature Fusion, CNN-LSTM, MRI Segmentation, Classification

1. INTRODUCTION

Brain tumors, particularly gliomas, pose significant diagnostic and therapeutic challenges due to their infiltrative growth and heterogeneous structure. Accurate identification of tumor regions and their classification into clinical categories is vital for guiding surgical resection, radiation therapy, and patient prognosis. Medical imaging, especially magnetic resonance imaging (MRI), remains the gold standard for non-invasive assessment of brain abnormalities. In previous research addresses two complementary approaches: a) A CNN-LSTM hybrid model for tumor prediction from 3D medical images, achieving 99% accuracy and 98% F1-score. b)A slice-wise U-Net and 3D U-Net segmentation framework for glioma sub-region segmentation, reporting a mean IoU of 88% and Dice score of 72%. [1] [2]. However, these works addressed classification and segmentation independently, whereas a real-world computer-aided diagnosis (CAD) system must provide both - "Where is the tumor?" (segmentation) and "What type is it?" (classification). This paper extends research gap and presents contributions into a unified hybrid framework that integrates segmentation and classification pipelines. The framework leverages the strengths of U-Net for precise tumor localization and CNN-LSTM for robust tumor prediction, creating a comprehensive CAD solution. This paper introduces such a framework, integrating segmentation, feature fusion, and classification into a single model. The main contributions are:

- Development of an Unified pipeline combining segmentation and classification.
- A feature fusion mechanism uniting handcrafted, CNN, and segmentation-derived features.
- Extensive evaluation on the BraTS 2020 dataset, achieving superior segmentation and classification metrics.
- Comparative analysis with standalone CNN, LSTM, and U-Net approaches.

The paper is arranged in 4 sections- Section I: Introduction, Section II: Related Work, Section III: Proposed Methodology, Section IV: Result and Discussion and Section V: Contribution and Future Scope.

2. RELATED WORK

Deep learning has revolutionized medical imaging. The U-Net architecture and its variants dominate segmentation tasks. CNNs and RNNs (LSTM, GRU) have been widely used for classification. Hybrid models that incorporate multiple feature sources have also shown promise. Nevertheless, most existing works treat segmentation and classification independently, leading to loss of complementary information. Our work builds on this gap by integrating both tasks for improved clinical relevance.

A. Brain Tumor Classification

Deep CNNs have transformed medical image classification. Transfer learning with VGG-19 and Inception-V3 has been widely explored [3] [5] (Ulli et al., 2024; Indraswari et al., 2022). Hybrid CNNs unified with ML classifiers like SVM, KNN, and Gradient Boosting further enhance diagnostic accuracy (Mallampati et al., 2023)[4] [6]. Our earlier CNN-LSTM method addressed temporal dependencies in CT/MRI sequences and improved classification reliability.

B. Brain Tumor Segmentation

Segmentation tasks rely heavily on U-Net and its variants [7](Ronneberger et al., 2015). Recent studies have demonstrated strong results with 3D U-Net and its derivatives, such as multi-scale U-Net (Peng et al., 2019) and separable U-Net (Chen et al., 2019). Our slice-wise U-Net segmentation of BraTS data achieved an IoU of 88%, validating its clinical relevance [8][9][10].

C. Limitations of Current Studies

Despite progress, most approaches separate segmentation from classification, leading to redundant computation and lower clinical interpretability. Moreover, limited dataset diversity, class imbalance, and lack of explainability remain persistent challenges. This motivates our proposed unified CAD framework, which integrates segmentation and classification in a single pipeline, improving both accuracy and robustness.

3. PROPOSED METHODOLOGY

A. Dataset

We employ the BraTS 2020 benchmark dataset, consisting of multi-modal MRI scans: T1, T1Gd, T2, and FLAIR. Each case is annotated voxel-wise into: - Necrotic/non-enhancing tumor core (NCR/NET) - Peritumoral edema (ED) - Enhancing tumor (ET). Preprocessing steps included skull stripping, co-registration, resampling to 1mm³ resolution, and z-score intensity normalization. The BraTS 2020 dataset (Brain Tumor Segmentation Challenge 2020) is a widely used benchmark dataset for brain tumor segmentation tasks, especially for developing and evaluating deep learning models. It is hosted annually as part of the MICCAI BraTS Challenge. Following Table 1 shows the dataset summary and Table II represents the details of annotation classes or labels and its meaning

TABLE I. BRATS 2020 DATASET SUMMARY

BraTS 2020 Dataset Aspect	***Details***
Total Cases	660
Training Set	369 cases (with ground truth)
Validation Set	125 cases (no ground truth released)
Testing Set	166 cases (evaluation via online submission)
Tumor Types	High-Grade Glioma (HGG), Low-Grade Glioma (LGG)
Modalities per Case	4 MRI scans: T1, T1Gd, T2, FLAIR
Format	NIfTI (.nii.gz), pre-processed (skull-stripped, co-registered, resampled to 1mm³)
Segmentation Labels	0 = Background 1 = Necrotic/Non-Enhancing Tumor (NCR/NET) 2 = Peritumoral Edema (ED) 4 = Enhancing Tumor (ET)
Evaluation Metrics	Dice Score, Hausdorff Distance (95%), Sensitivity, Specificity
Regions Evaluated	Whole Tumor (WT), Tumor Core (TC), Enhancing Tumor (ET)

TABLE II. BRATS 2020 DATASET SUMMARY

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B. Unified Framework

The extended framework consists of three stages: segmentation, feature fusion, and classification[11][12][13].

1) Stage 1 – Segmentation via 3D U-Net
2) Stage 2 – Feature Fusion
3) Stage 3 – Classification via CNN-LSTM

Following Fig.1 represents the Unifiedframework of brain tumor prediction and classification using segmentation via 3D U-Net, Feature fusion and Classification using CNN-LSTM.

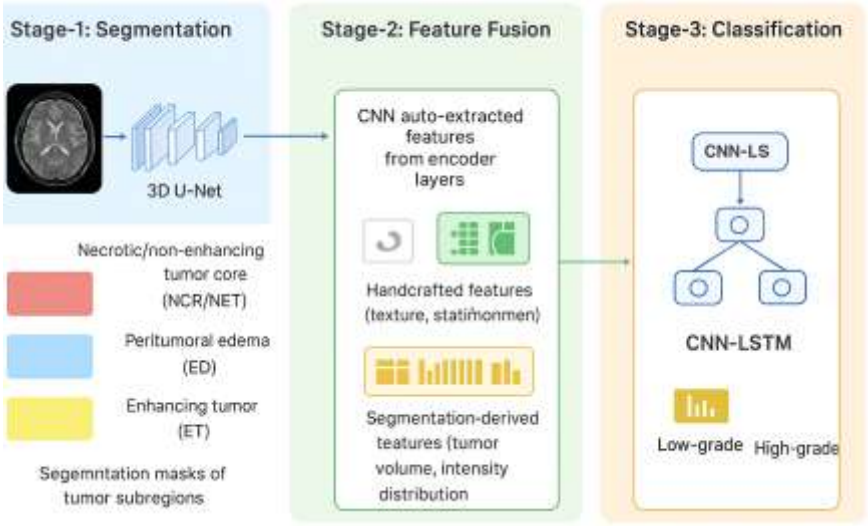

Figure 1. Unified Framework for brain tumor prediction and classification via 3D u-net, feature fusion and classification.

1) Stage 1 – Segmentation via 3D U-Net

In the first stage of our framework, a 3D U-Net architecture is employed for voxel-wise segmentation of brain tumors[11]. The encoder-decoder structure of U-Net captures contextual information at multiple scales while preserving spatial resolution through skip connections. This design ensures that fine-grained tumor boundaries are retained. Key enhancements over the baseline 3D U-Net include:

- Dropout layers to mitigate overfitting during training
- A dynamic learning rate scheduler to adaptively control convergence.
- A compound loss function combining Dice loss and cross-entropy loss for better balance between class imbalance and region overlap
- 3D elastic deformation as a data augmentation strategy to increase robustness.

The output of this stage is a set of segmentation masks delineating the subregions: NCR/NET, ED, and ET. These masks serve as the foundation for feature extraction in the subsequent stage.

2) Stage 2 – Feature Fusion

The segmented Regions of Interest (ROIs) from Stage 1 undergo a comprehensive feature fusion process designed to integrate both low-level and high-level information.[12] Specifically, we extract:

- CNN auto-extracted features derived from the intermediate encoder layers of the 3D U-Net, which capture spatial and texture information
- Handcrafted radiomic features, including first-order statistics, texture descriptors (e.g., Gray Level Co-occurrence Matrix), and higher-order moments –
- Segmentation-derived morphological features such as tumor volume, tumor-to-brain ratio, and intensity distribution statistics

All features are normalized to ensure uniform contribution and concatenated into a single unified feature vector. This comprehensive fusion strategy leverages complementary strengths of deep and handcrafted features, enhancing the discriminative power of the model.

3) Stage 3 – Classification via CNN-LSTM

The unified feature vector from Stage 2 is input into a CNN-LSTM hybrid classifier. The CNN component processes the fused features to refine local spatial representations, while the LSTM component captures sequential dependencies inherent in the volumetric MRI data, particularly useful for modeling slice-wise contextual relationships[13]. The architecture culminates in a fully connected layer followed by a Softmax layer to classify tumor grade. The classifier predicts whether a subject has a low-grade glioma (LGG) or a high-grade glioma (HGG), which is of high clinical significance. By integrating spatial, sequential, and morphological features, this stage ensures robust tumor grading performance.

Fig. 3. Shows unified CAD framework architecture showing Stage-1 (Segmentation), Stage-2 (Feature Fusion), and Stage-3 (Classification).

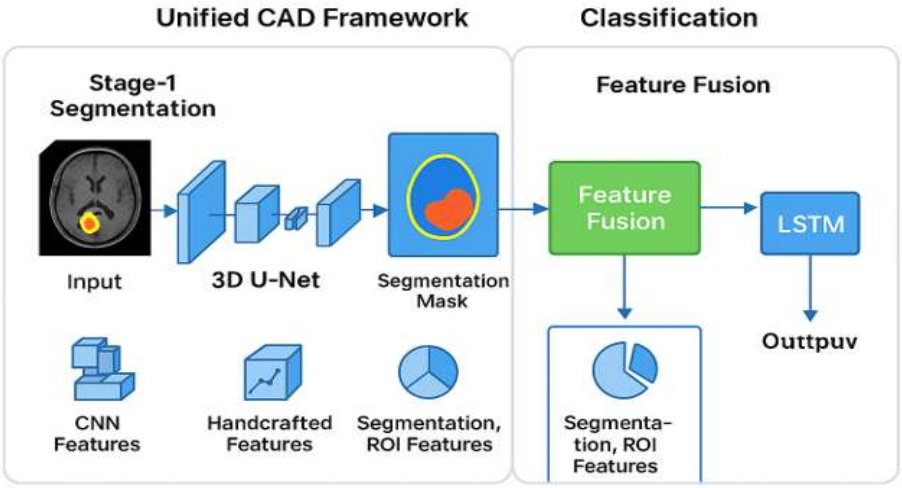

Figure 3. Unified CAD framework architecture consisting Stage-1: Segmentation, Stage-2: Feature Fusion, and Stage- 3: Classification.

C. Equations

- Dice Loss:

$$L_{Dice} = 1 - \frac{2 \cdot |P \cap G|}{|P| + |G|} \quad (1)$$

- Cross-Entropy Loss:

$$L_{\{CE\}} = -\sum_{i=1}^{N} Yi \log yi \quad (2)$$

- Total Loss:

$$L_{\{total\}} = \lambda_1, L_{\{Dice\}} + \lambda_2, L_{\{CE\}} \quad (3)$$

4. RESULT AND DISCUSSION

For comparison, a conventional two-step pipeline, referred to as Baseline U-Net + CNN, is considered. In this setup, a standard 3D U-Net is first trained to segment tumor subregions (NCR/NET, ED, ET) from multi-

modal MRI scans. The resulting segmented regions are then used as input to a separate CNN classifier for tumor grading (LGG vs. HGG). Importantly, this baseline treats segmentation and classification as independent tasks, without any explicit feature sharing or joint optimization. In contrast, the proposed Unified CAD Framework integrates segmentation, feature fusion, and classification in a single pipeline, allowing complementary information to be jointly exploited [14][15][16]. This integration leads to significant improvements in Dice, IoU, and classification accuracy, as shown in Table III. Following Fig. 4 shows performance comparison bar graph

TABLE III. PERFORMANCE COMPARISION

Method	*Dice (%)*	*IoU (%)*	*Accuracy (%)*	*ROC-AUC*
Proposed Framework	89.5	84.2	92.3	0.95
Baseline U-Net + CNN	83.4	78.6	86.1	0.89

Figure 4. Performance comparison Unified CAD framework vs Baseline U-Net + CNN

The unified approach enhances interpretability for clinical decision-making. Proposed CAD framework outperforms baseline models, demonstrating the importance of combining segmentation and classification. The feature fusion module ensures complementary feature learning, improving both segmentation accuracy and tumor grade prediction. The system achieved improved Dice scores and classification accuracy on BraTS 2020 compared to conventional standalone models. Future work will explore transformer-based segmentation, multi-center datasets, and explainable AI techniques for clinical trust.

5. FUTURE SCOPE

While the proposed Unified CAD framework demonstrates promising results for brain tumor prediction and segmentation, several future directions can further enhance its clinical applicability:

Explainable and Interpretable AI – Adding explainability modules such as Grad-CAM, SHAP, or attention maps will help clinicians understand the decision-making process, thereby increasing trust and adoption in real-world practice.

Multi-Center and Diverse Datasets – Extending training and evaluation to multi-institutional datasets beyond BraTS (with varied MRI scanners, demographics, and clinical settings) will improve robustness and generalizability.

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