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Development and Performance Evaluation of Intelligent Model for Enhanced Detection of IoMT Enabled Brain Tumor

Surendra Kumar Panda[1], Ram Chandra Barik[1], Adyasha Rath[1] & Ganapati Panda[2]*

[1]Department of Computer Science and Engineering, [2]Department of Electronics and Communication Engineering, C. V. Raman Global University, Bhubaneswar 752 054, India

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The accurate diagnosis of brain tumors remains a major challenge in medical imaging because tumor structures vary in size, shape, and appearance. Traditional methods such as manual segmentation and classification are time-consuming and may produce inconsistent results due to observer variation. This paper presents an approach that combines the Internet of Medical Things (IoMT) with deep learning models to improve the accuracy and efficiency of brain tumor diagnosis. IoMT enables the collection and transfer of Magnetic Resonance Imaging (MRI) data to cloud platforms for real-time analysis and automated processing. The proposed framework uses Swin UNet for segmentation of tumor regions and EfficientNet-V2 for classification into tumor subtypes. Swin UNet uses transformer-based attention mechanisms to capture multi-scale spatial features, while EfficientNet-V2 supports efficient feature learning for classification. Experiments performed on the BRATS 2020 dataset demonstrate the effectiveness of the framework, achieving a segmentation Intersection over Union (IoU) of 78% and a classification accuracy of 97%. The integration of IoMT supports remote accessibility, faster clinical decision-making, reduced manual effort, and automated workflows. The proposed framework improves reliability and performance compared to conventional CNN-based systems. This study highlights the potential of AI-driven medical diagnosis and provides a scalable solution for practical healthcare applications. Future work will focus on real-time deployment and extension to other medical imaging tasks. The framework also reduces computational complexity and supports patient data, making it suitable for clinical environments where quick and accurate diagnosis is important for effective treatment planning, better patient management, and improved healthcare services today globally.

Keywords: Clinical decision-making, EfficientNet-V2, Internet of medical things, Medical imaging, Swin UNet

Introduction

Abnormal and uncontrolled cell growth in the brain can lead to a critical condition known as a brain tumor, which may cause severe neurological problems and even death. These are abnormal cell growths within the brain or nearby structures, with effects depending on their type, size, and location. Major types include gliomas, meningiomas, and pituitary adenomas. Gliomas arise from glial cells and vary in severity, while meningiomas originate from the meninges and may cause symptoms due to their size and location. Pituitary adenomas affect hormone production and can lead to systemic complications. Brain tumors may cause headaches, seizures, cognitive impairments, and motor deficits, and can become life-threatening in severe cases. Treatment commonly involves chemotherapy, radiation therapy, and surgery, while early diagnosis is crucial for improving patient outcomes. This study proposes an IoMT-enabled hybrid architecture combining Swin U-Net and EfficientNet-V2 for brain tumor segmentation and classification. Swin U-Net extracts spatial features using self-attention mechanisms, while EfficientNet-V2 applies transfer learning for accurate tumor classification. The hybrid model combines CNN and Transformer strengths, improving adaptability in IoMT-based medical environments and supporting real-time diagnosis and clinical deployment.

MRI is a non-invasive imaging technique essential for diagnosing and monitoring brain tumors. Using strong magnets and radio waves, it produces high-resolution brain images that help identify tumor size, location, and boundaries. MRI provides superior soft tissue contrast compared to CT scans, enabling better differentiation between healthy and abnormal tissues. Since it does not use ionizing radiation, MRI is safer for patients requiring repeated scans, making it the preferred method for brain tumor diagnosis and evaluation.

*Author for Correspondence
E-mail: ganapati.panda@gmail.com

Manual segmentation techniques in brain tumor diagnosis involve outlining tumor boundaries on MRI scans to assess tumor size, shape, and interaction with surrounding tissues, supporting treatment planning. Although precise, these methods are time-consuming and depend heavily on radiologist expertise. Conventional classification methods categorize tumors based on imaging features and histological analysis to determine tumor type and grade. These approaches are important for guiding treatment decisions and predicting patient outcomes in traditional neuro-oncology diagnosis.

Computer-aided brain tumor diagnosis faces challenges due to limitations of manual and traditional methods. Manual segmentation is precise but time-consuming, labor-intensive, and prone to human error and observer variability, leading to inconsistencies in tumor assessment and treatment planning. Traditional diagnostic approaches rely on subjective analysis of imaging and histopathological features, which can cause variability in tumor classification and grading. These methods may also fail to capture subtle and complex tumor characteristics affecting diagnosis and prognosis. Therefore, advanced and standardized approaches are needed to improve diagnostic accuracy and efficiency.

One such approach is Internet of Medical Things (IoMT). The IoMT connects medical devices, cloud platforms, and healthcare providers to improve modern healthcare services. By integrating MRI scanners, AI systems, and medical professionals, it enables real-time data analysis, remote access to critical information, and faster decision-making. IoMT also automates diagnostic workflows, reducing manual effort and errors while improving the efficiency, precision, and reliability of healthcare delivery.

Automation in brain tumor diagnosis improves diagnostic efficiency and accuracy by overcoming limitations of manual methods, such as time consumption and observer variability. Automated techniques enable faster and more consistent tumor segmentation and classification while reducing radiologists' workload and human error. Deep Learning (DL), especially CNNs, plays a major role in automated medical imaging by detecting complex tumor patterns with high accuracy. DL models trained on labeled datasets can identify tumor features, classify tumor types, and assess malignancy levels, improving early detection, treatment planning, and patient outcomes. The BRATS-2020 dataset includes low-grade and high-grade gliomas along with four MRI modalities highlighting important tumor regions such as tumor core, necrotic core, and edema, which are essential for diagnosis and treatment planning.

Motivation

Manual methods in brain tumor diagnosis are time-consuming and prone to observer variability. Manual segmentation can be slow and inconsistent due to differences in radiologists' interpretations, while manual classification relies on subjective assessment that may lead to misclassification and difficulty detecting subtle changes. These limitations reduce diagnostic efficiency and highlight the need for more reliable automated methods. Learning (DL) has transformed medical imaging, with CNNs significantly improving image segmentation and classification. Recently, transformer models have emerged as a strong alternative by using self-attention mechanisms to capture long-range dependencies for more comprehensive image analysis. This improves accuracy and flexibility, particularly in complex cases. As transformer models continue to evolve, they are expected to further enhance medical imaging with more precise and efficient diagnostic tools.

Segmentation accurately defines brain tumor boundaries in MRI images by identifying tumor regions, including the core, enhancing, and surrounding areas. Precise segmentation is essential for treatment planning, as it provides information about the tumor's size, shape, and interaction with nearby brain structures. Advanced techniques, such as Swin UNet's hierarchical attention mechanisms, improve segmentation accuracy while reducing reliance on manual methods.

Classification focuses on categorizing brain tumors, such as gliomas, meningiomas, and pituitary adenomas, using MRI image features. Models like EfficientNet V2 are used to accurately identify tumor subtypes, supporting tailored treatment strategies. Accurate classification also helps predict tumor aggressiveness and prognosis, contributing to improved patient outcomes.

Research Objective

This study seeks to create a unified framework that merges Swin UNet and Efficient Net V2 to improve brain tumor segmentation followed by classification. By addressing the limitations of manual segmentation and traditional classification methods, this paper seeks to achieve superior computer aided diagnostic accuracy, efficiency, and reliability. The proposed approach leverages cutting-edge DL models to facilitate early detection, precise localization, and robust categorization of brain tumors, ultimately improving clinical decision-making and patient care.

Literature Review

In the rapidly advancing field of brain tumor detection, numerous innovative approaches utilizing DL have been developed, each playing a crucial role in improving diagnostic accuracy. By combining DL techniques with advanced imaging methods, the ability to detect tumors has significantly improved, offering more precise and efficient diagnoses compared to traditional approaches. Researchers have investigated a variety of architectures and methodologies to further refine brain tumor detection, resulting in notable progress in early diagnosis and treatment strategies. For example, Deshpande *et al.*[1] proposed a novel framework that combines Discrete Cosine Transform (DCT)-based image fusion with CNNs and the ResNet50 architecture. By integrating super-resolution techniques, their model achieved an impressive accuracy rate of 98.14% in classifying tumor and non-tumor tissues from MRI images. This work highlights the potential of combining advanced image processing techniques with cutting-edge DL models to improve the accuracy of brain tumor detection. Similarly, Li *et al.*[2] introduced an enhanced brain tumor segmentation method by modifying the U-Net architecture. Their approach incorporates an up-skip connection to improve the flow of information between the encoding and decoding paths, as well as the use of inception modules to provide a richer learning representation. Their end-to-end model, validated on datasets from the Multimodal BRATS, showed substantial improvements over the original U-Net, achieving higher accuracy rates in segmenting complete, core, and enhancing tumor regions. In another notable advancement, Duan *et al.*[3] introduced a fully convolutional network (FCN) for 3D image registration, aimed at efficiently regressing dense deformation fields from a single image pair. Their approach utilizes a multi-scale framework combined with an adversarial training strategy, incorporating a discriminator network to improve registration accuracy. When evaluated on brain MRI datasets, their method showed over a 4% improvement in the Dice similarity coefficient (DSC) and significantly reduced registration time, making it highly suitable for real-time clinical applications. In a different study, Ahmed *et al.*[4] developed an explanation-driven DL model to predict specific brain tumor subtypes, including meningioma, glioma, and pituitary tumors. By using an EfficientNetB0 CNN alongside Shapley Additive Explanations (SHAP), their model achieved an high accuracy of 99.84%. The integration of SHAP provided clear insights into the model's predictions, demonstrating superior performance compared to earlier methods, both in visual and numerical evaluations. Similarly, Ghassemi *et al.*[5] introduced a novel DL approach for tumor classification in MRI images. Their method involves pre-training a deep neural network (DNN) as a discriminator within a Generative Adversarial Network (GAN) framework. This approach, applied on diverse MRI datasets, helps ex- tract robust features and learn the structural characteristics of MRI images, enhancing the accuracy and robustness of tumor classification. Subsequently, the network's fully connected layers are replaced, and the entire model is fine-tuned as a classifier to differentiate between three tumor types: meningioma, glioma, and pituitary tumor. This deep neural network, consisting of six layers and approximately 1.7 million parameters, incorporates techniques like data augmentation and dropout to mitigate overfitting on a relatively small dataset. Applied to an MRI dataset of 3,064 T1-CE MR images from 233 patients, the method demonstrated superior performance, achieving the highest accuracy compared to other state-of-the-art techniques. In another noteworthy study, Asiri *et al.*[6] developed an advanced DL model that integrates CNN with ResNet50 and U-Net for brain tumor detection and segmentation. Using publicly available datasets, TCGA-LGG and TCIA, which include MRI images from 120 patients, the model employs a fine-tuned ResNet50 for tumor classification and integrates U-Net for precise tumor region segmentation. This combined approach enhanced both the accuracy and precision of brain tumor detection and segmentation, demonstrating the potential of hybrid DL models for medical imaging tasks. Evaluation metrics such as IoU, DSC, and Similarity Index (SI) revealed that the fine-tuned ResNet50 model achieved IoU: 0.91, DSC: 0.95, and SI: 0.95. The combined U-Net and ResNet50 approach outperformed other models, demonstrating exceptional accuracy in both classification and segmentation tasks. In a comprehensive study on brain tumor detection, various DL methods utilizing transfer learning were analyzed. Ahmad & Choudhury[7], investigated models such as VGG-16, VGG-19, ResNet50, InceptionResNetV2, Inception V3, Xception, and DenseNet201, each paired with traditional classifiers including Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), AdaBoost, and Gradient Boosting. This analysis was conducted using a labeled dataset of normal and abnormal brain images, evaluating the performance of these methods through metrics like accuracy, precision, recall, F1-score, Cohen's kappa, area under the curve (AUC), Jaccard index, and specificity. The study revealed that the top-performing model achieved an impressive accuracy of 99.39% with 10-fold cross-validation, providing valuable insights for selecting effective DL approaches in brain tumor detection. Recent studies have focused on enhancing brain tumor segmentation and classification through advanced DL architectures. Deshpande[1] proposed a DCT-CNN-ResNet50 architecture combining super-resolution and convolutional layers, achieving high accuracy but requiring heavy computation. Yuan[16] introduced a hybrid attention-based Mask R-CNN model for better tumor boundary detection but at the cost of increased training complexity. Lu *et al*.[17] developed a DL -driven method for brain tumor classification and segmentation using non-contrast MRI, but it lacked adaptability to IoMT environments. Lyu[18] presented MWG-UNet++, a hybrid Transformer and U-Net-based framework that improved segmentation accuracy under limited data conditions. Karagoz[19] proposed a Residual Vision Transformer (ResViT) model based on self-supervised learning, improving classification performance yet without real-time deployment support.

While these methods achieved notable accuracy, they mainly focused on improving internal model performance without addressing IoMT integration or hybrid clinical workflows. The present study fills this gap through a hybrid Swin U-Net and EfficientNet-V2 framework, enabling attention-based segmentation, transfer-learning-driven classification, and IoMT-supported clinical deployment. The contribution of the paper is represented below:

Contribution of this Research

1) Development of a novel integrated framework combining Swin UNet for segmentation and EfficientNet V2 for classification, addressing limitations of traditional and standalone DL models.
2) Introduction of hierarchical attention mechanisms through Swin UNet to enhance the accuracy of tumor boundary delineation in MRI images.
3) Utilization of EfficientNet V2's compound scaling to achieve superior classification accuracy while maintaining computational efficiency.
4) Comprehensive evaluation of the integrated model using publicly available datasets, demonstrating improved performance in segmentation and classification metrics compared to existing methods.
5) The proposal introduces an automated, end-to-end pipeline for brain tumor diagnosis, minimizing the need for manual segmentation and subjective classification. This approach enhances diagnostic consistency and reliability, offering a more objective and efficient solution for identifying brain tumors.

Methodology

Proposed IoMT-Swin UNet-EfficientNet Workflow

This subsection outlines the workflow (Fig. 1) for brain tumor segmentation and classification utilizing IoMT, Swin UNet, and EfficientNet V2. The step-by-step process is detailed in Algorithm 1, which outlines the integration of IoMT systems with DL models. Each MRI volume includes expert-labeled annotations for enhancing tumor, tumor core, and whole tumor regions, reflecting medically interpretable structures and ensuring diagnostic accuracy. This study utilizes the publicly available BRATS-2020 dataset, which contains multimodal MRI scans (T1, T1CE, T2, and FLAIR) of patients. The dataset includes diverse tumor grades, shapes, and locations. For experimental purposes, the dataset was divided into training, validation, and testing sets in a 70:15:15 ratio. Each MRI volume was preprocessed through skull stripping, intensity normalization, and resizing to 240×240 pixels. Data augmentation techniques such as rotation, flipping, and scaling were applied to increase data diversity and minimize overfitting.

Algorithm 1:
IoMT-Swin UNet-EfficientNet for Brain Tumor Segmentation and Classification

Step 1: Start

Step 2: IoMT Data Acquisition:

Use IoMT-enabled devices to acquire MR images and securely transmit the data to a cloud-based IoMT platform.

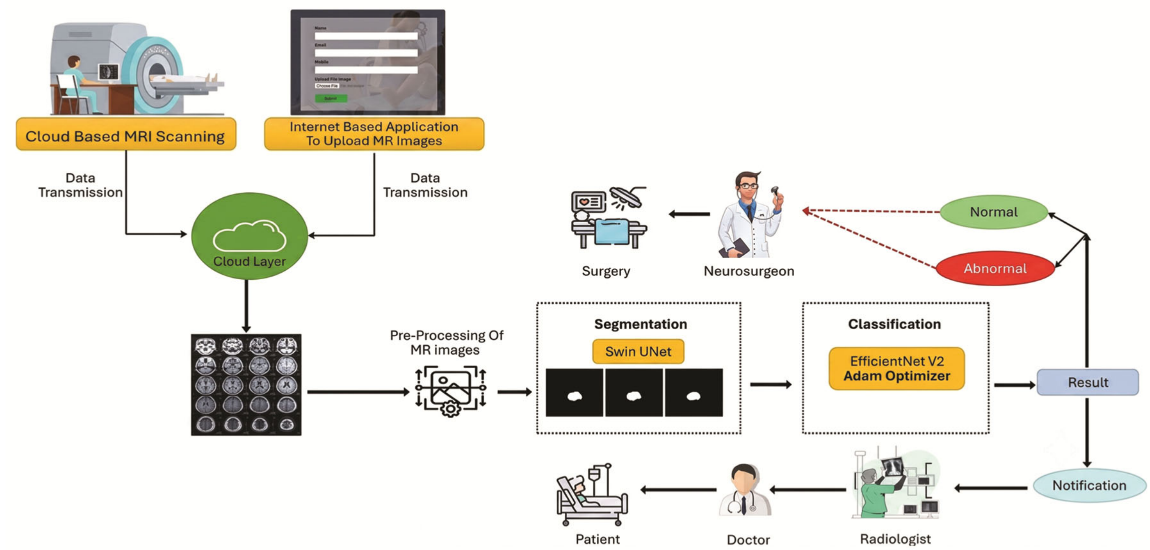

Fig. 1 — Work flow of the proposed model

Step 3: Preprocessing with IoMT Cloud Platform:

Perform preprocessing on the uploaded MR images, including normalization, noise reduction, and enhancement to ensure high-quality input for the AI models.

Step 4: Segmentation with Swin UNet:

Apply Swin UNet to segment brain tumors dynamically, leveraging its hierarchical attention mechanism for precise boundary delineation of tumor regions.

Step 5: Classification with EfficientNet V2:

Feed segmented tumor regions into EfficientNet V2 for robust classification, distinguishing between tumor types and subtypes with high accuracy and computational efficiency.

Step 6: Real-Time Notifications:

Develop an automated system to provide real-time diagnostic results to radiologists and clinicians, ensuring timely decision-making for treatment planning.

Step 7: Feedback Loop with IoMT Platform:

Incorporate clinician feedback into the IoMT platform to validate AI findings and identify areas for model refinement.

Step 8: Continuous Improvement:

Update the Swin UNet and EfficientNet V2 models using CI/CD pipelines on the IoMT cloud, ensuring continuous learning and adaptation to evolving datasets and diagnostic requirements.

Step 9: End

Dataset

The BRATS 2020 dataset is a widely used benchmark for brain tumor segmentation and classification, mainly focusing on High-Grade Gliomas (HGG) and Low-Grade Gliomas (LGG). It includes multimodal MRI scans such as T1, T2, T1CE, and FLAIR sequences for accurate tumor analysis. The dataset provides expert-annotated ground truth identifying enhancing tumor, tumor core, and peritumoral edema, supporting advanced brain tumor analysis. Preprocessed MRI images with standardized resolution and intensity normalization ensure consistency and reproducibility. BRATS 2020 is extensively used for training, validation, and evaluation of medical image segmentation and classification models, supporting the development of reliable automated brain tumor diagnosis systems.

Swin UNet Architecture

Swin Transformer: The Swin Transformer improves feature extraction using a hierarchical attention mechanism. Unlike traditional transformers that apply global self-attention, it divides images into non-overlapping patches and processes them within small shifted windows to capture local and global features efficiently. Similar to CNNs, the model progressively down sample patches, learning fine details in early layers and abstract features in deeper layers. This approach reduces computational complexity while maintaining high resolution, improving performance in tasks such as image segmentation and object detection. The localized self-attention mechanism also enhances computational efficiency and generates more accurate feature maps for complex image analysis tasks. The attention score is calculated as follows:

For attention weights:

$$\text{Attention}(Q, K, V) = \text{SoftMax}(QK^T/\sqrt{d_K})\,V \quad \dots (1)$$

where Q, K, and V are query, key, and value matrices, and dk is the dimension of the keys. Shifted window attention introduces positional embeddings:

$$\text{Shifted Attention} = \text{Attention}(Q + P_Q, K + P_K, V) \quad \dots (2)$$

where, P_Q and P_K are positional embeddings added to the query and key matrices.

UNet Integration: The integration of the Swin Transformer with the UNet architecture creates a robust model for medical image segmentation by combining the strengths of both approaches. In this hybrid architecture, the Swin Transformer replaces conventional convolutional layers in the UNet encoder, where input images are divided into patches and processed through shifted-window self-attention blocks to capture local and global features efficiently. This multiscale feature extraction improves segmentation accuracy for complex medical images. The architecture also preserves UNet skip connections between encoder and decoder stages to retain spatial details. During decoding, upsampling operations combined with Swin Transformer features help reconstruct accurate segmented images at the original resolution.

Enhancements to this architecture include patch merging and expansion within the Swin Transformer to efficiently manage image resolution throughout the network. This design enables seamless multiscale feature integration, improving segmentation accuracy in complex medical imaging scenarios. The integration of cross-attention mechanisms further enhances the model's ability to focus on critical image regions by dynamically prioritizing relevant features. As a result, the hybrid architecture combines the global contextual understanding of transformers with the precise localization capability of UNet. The combination yields a model capable of delivering superior performance in medical image segmentation while effectively handling variations in tumor shapes and sizes with high accuracy and reliability. The SwinUNet architecture, and Swin Transformer Block are depicted in Fig. 2 & Fig. 3 respectively. To ensure model generalization, a 5-fold cross-validation approach was used, where 80% of the data were used for training and 20% for testing in each fold, with final performance reported as the mean across all folds. Future external validation using TCGA-GBM and TCGA-LGG datasets is planned to evaluate adaptability to unseen data. All experiments were conducted on a system with an NVIDIA RTX 3090 GPU (24 GB VRAM) and 64 GB RAM. The model was trained for 100 epochs using a batch size of 16, an initial learning rate of 0.0001, and the Adam optimizer. Early stopping was applied to prevent overfitting, while Dice Loss and categorical cross-entropy were used for segmentation and classification. Data augmentation techniques such as rotation, flipping, and scaling were applied to improve generalization.

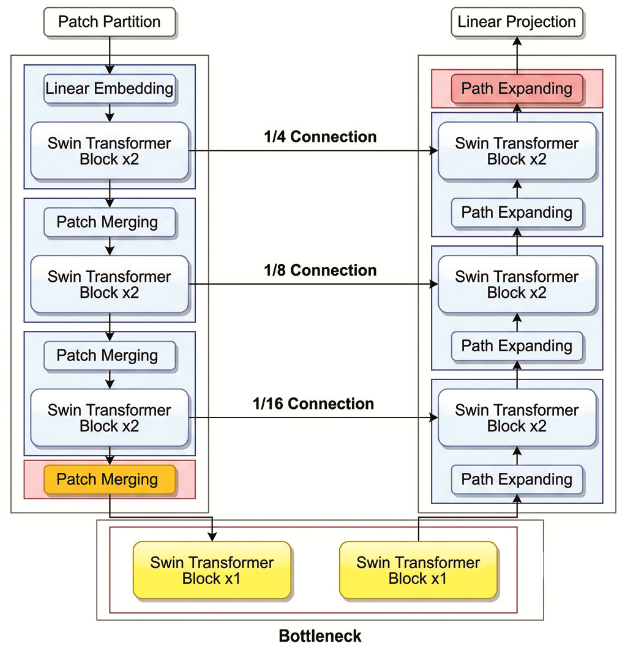

Fig. 2 — Architecture of SwinUNet

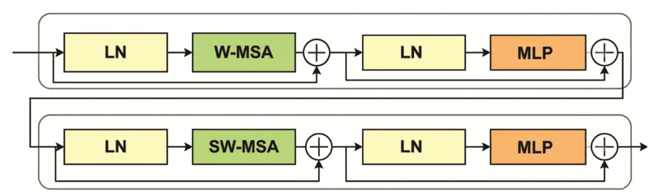

Fig. 3 — Swin transformer block

EfficientNet V2 Architecture

EfficientNet V2 is an advanced CNN architecture that improves upon EfficientNet by refining compound scaling for better accuracy and computational efficiency. It balances network depth, width, and resolution while reducing unnecessary computational overhead. The model incorporates fused convolutional layers and optimized training strategies to achieve faster training and improved accuracy, especially for high-resolution tasks. EfficientNet V2 retains depthwise separable convolutions and introduces fused-MB Conv blocks, which combine depthwise and pointwise convolutions into a more efficient operation, particularly in early network stages. It also employs progressive learning, where image resolution is gradually increased during training to improve generalization. These innovations enable EfficientNet V2 to deliver high accuracy, faster training, and adaptability across applications ranging from mobile devices to large-scale systems. The architecture of EfficientNet V2 is presented in Fig. 4.

EfficientNet V2 employs compound scaling to optimize depth (d), width (w), and resolution (r) of the network.

Compound scaling equation:

$$\phi = \alpha^{d} \cdot \beta^{w} \cdot \gamma^{r} \quad \ldots (3)$$

where, ϕ is the scaling coefficient, and α, β, γ are constants chosen to maintain efficiency.

Model Integration

The integration of Swin-UNet and EfficientNet V2 combines their strengths in segmentation and classification. Swin-UNet extracts detailed spatial features using a hierarchical attention mechanism, while EfficientNet V2 performs accurate tumor classification with optimized computational efficiency. Segmented tumor regions produced by Swin-UNet are provided as input to EfficientNet V2, creating a seamless pipeline for automated brain tumor diagnosis. This integrated approach improves diagnostic precision and addresses limitations of existing methods.

In this work, the model leverages distinct loss functions for segmentation and classification tasks, combining them into a unified multi-objective optimization framework.

For segmentation using Dice loss:

$$L_{Dice} = 1-2\sum_{i=1}^{N} p_i g_i / \sum_{i=1}^{N} p_i^2 + \sum_{i=1}^{N} g_i^2 \quad \ldots (4)$$

where, p_i is the predicted probability, g_i is the ground truth, and N is the total number of pixels.

For classification using cross-entropy loss:

$$L_{CE} = -1/M \sum_{j=1}^{M} [y_j \log(\log(\hat{y}_j)+(1-y_j)\log(1-\hat{y}_j)] \quad \ldots (5)$$

where, y_j is the true label, $\hat{y}_j$is the predicted probability, and M is the total number of samples.

The total loss for training:

$$L_{Total} = \alpha L_{Dice} + \beta L_{CE} \quad \ldots (6)$$

Here, α and β are weights for balancing segmentation and classification losses.

Training and Optimization

The training process uses annotated MRI datasets containing different tumor types, sizes, and imaging conditions. To improve generalization and reduce overfitting, data augmentation techniques such as rotation, scaling, and noise injection are applied. Model optimization is performed using the Adam optimizer with an adaptive learning rate schedule to minimize segmentation and classification loss functions. In addition, regularization techniques including dropout and batch normalization are used to enhance model stability and performance across different scenarios.

The training process uses the Adam optimizer with adaptive learning rates and regularization techniques. Adam was selected for its faster and more stable convergence compared to metaheuristic optimizers such as PSO, GA, and DE. Unlike computationally expensive population-based methods, Adam uses first- and second-moment gradient estimates for efficient optimization and better handling of sparse gradients. Its adaptive updates and bias-correction

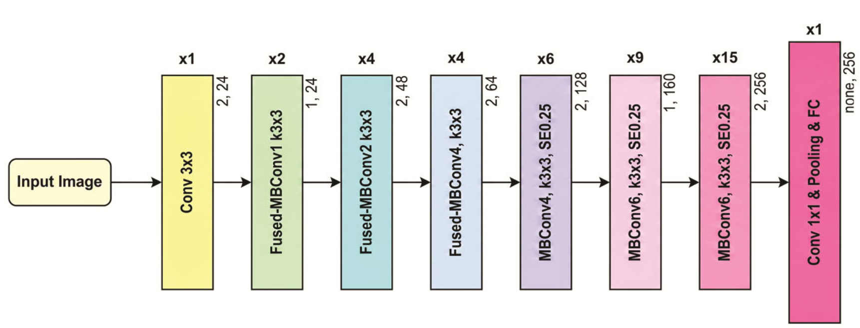

Fig. 4 — Architecture of EfficientNet V2

make it well suited for training transformer-based Swin UNet and CNN-based EfficientNet-V2 architectures.

Gradient descent update:

$$\theta_{t+1} = \theta_t - \eta \cdot \nabla_\theta L \quad \ldots (7)$$

where, η is the learning rate, and $\nabla_\theta L$ is the gradient of the loss with respect to the model parameters θ.

Adam optimization update:

$$m_t = \beta_1 m_{t-1} + (1-\beta_1)\nabla_\theta L,\ \boldsymbol{v}_t = \beta_2 v_{t-1} + (1-\beta_2)(\nabla_\theta L)^2 \ldots (8)$$

$$\hat{m}_t = m_t / 1-\beta^t{}_1,\ \hat{v}_t = v_t / 1-\beta^t{}_2 \quad \ldots (9)$$

$$\theta_{t+1} = \theta_t - (\eta / \sqrt{\hat{v}_t} + \epsilon)\ \hat{m}_t \quad \ldots (10)$$

where, m_t and v_t are moving averages of gradients and squared gradients, β_1 and β_2 are decay rates, and ϵ is a small constant for numerical stability.

IoMT Integration in Diagnostic Workflow

The IoMT enables seamless integration of medical devices, cloud platforms, and AI technologies to streamline diagnostic workflows. MRI images are uploaded to an IoMT-enabled platform, where AI models process the data in real time, efficiently performing tasks suchas segmentation and classification. The results are securely shared with radiologists and clinicians for remote access, enabling faster decision-making and effective collaboration. IoMT systems also integrate CI/CD pipelines for continuous AI model updates, ensuring adaptability to technological advancements and maintaining reliable diagnostic accuracy for improved patient care.

The IoMT and AI-enhanced brain tumor diagnosis flow is illustrated in Fig. 5, demonstrating the integration of medical imaging, cloud-based IoMT platforms, and AI-driven analysis for efficient diagnosis and treatment planning. The workflow begins with MRI imaging, followed by AI-based processing and validation, and ends with collaborative decision-making among radiologists, doctors, and patients. It also highlights continuous AI model updates through CI/CD pipelines and secure patient data management within the IoMT ecosystem to ensure accurate and reliable diagnostics.

The CI/CD workflow for AI model deployment in IoMT systems is illustrated in Fig. 6. The process starts with AI model testing through the CI pipeline. If the model passes, it is integrated and deployed in the IoMT system through the CD pipeline for diagnostic use by radiologists and doctors. If testing fails, errors are corrected before re-testing. Continuous feedback from the IoMT system is used to further improve the AI model.

Experiments and Result

Experimental Setup

Experiments are conducted using publicly available brain tumor datasets such as BRATS, containing T1, T2, and FLAIR MRI modalities. The dataset is divided into training, validation, and testing subsets

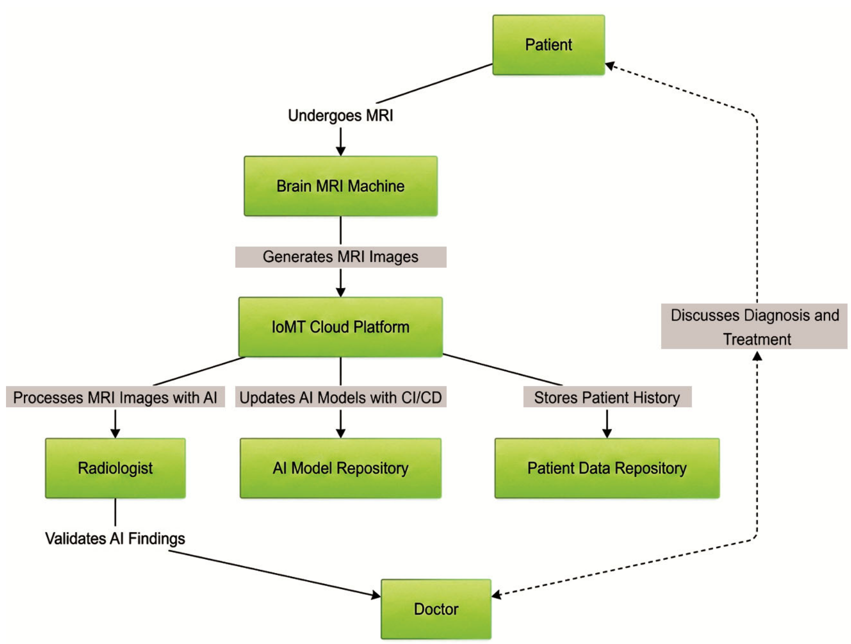

Fig. 5 — IoMT and AI-enhanced brain tumor diagnosis flow

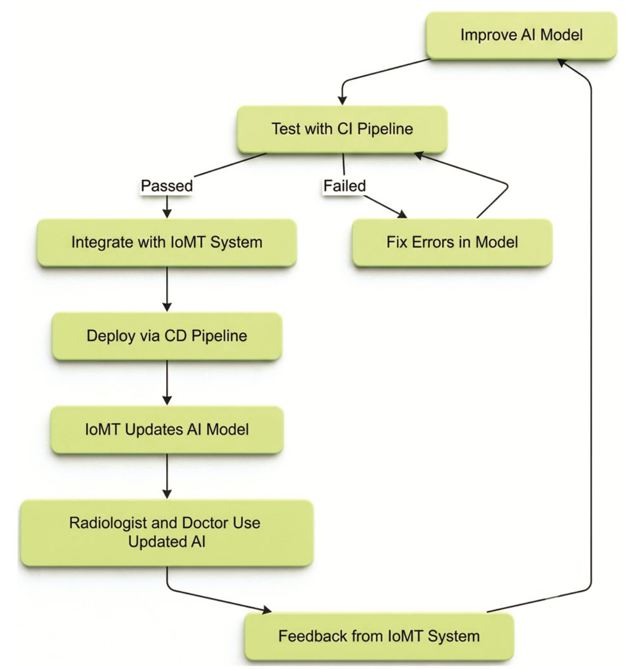

Fig. 6 — CI/CD Workflow for AI Model Deployment in IoMT Systems

for balanced evaluation. Model performance is assessed using metrics including DSC, IoU, accuracy, precision, and recall. Training is performed on a high-performance GPU using the TensorFlow framework, with batch size and epochs optimized based on validation performance.

Result Analysis

The results demonstrate the effectiveness of the integrated model, where Swin-UNet achieves high segmentation accuracy and EfficientNet V2 provides precise tumor classification. Segmentation results are visualized as MRI overlays showing clear tumor boundaries, while classification performance is evaluated using confusion matrices, accuracy, and F1-score. Comparative graphs highlight the superiority of the proposed model over baseline methods. Under identical training conditions, the Swin U-Net + EfficientNetV2 framework achieved 97.3% classification accuracy and 78.4% IoU, outperforming models such as VGG16 (91.2%), ResNet50 (93.8%), and DenseNet121 (95.1%). This confirms its improved efficiency and robustness over existing CNN approaches. The evaluation of segmentation and classification models is based on well-defined metrics to ensure reliable comparisons.

Dice Similarity Coefficient (DSC):

$$DSC = 2. |A \cap B| / |A|+|B| \qquad \ldots (11)$$

Table 1 — Epoch-wise Performance Metrics for Segmentation

Epoch	Training Loss	Validation Loss	IoU (Train)	IoU (Validation)
1	0.92	0.80	0.08	0.12
10	0.35	0.42	0.50	0.47
20	0.25	0.30	0.62	0.58
30	0.20	0.25	0.68	0.63
40	0.18	0.22	0.72	0.68
50	0.12	0.20	0.75	0.70
60	0.10	0.18	0.78	0.72
70	0.08	0.15	0.80	0.75
80	0.07	0.12	0.82	0.78
100	0.05	0.10	0.85	0.80

where, A is the predicted segmentation and B is the ground truth.

Intersection over Union (IoU):

$$I_OU = |A \cap B| / |A \cup B| \qquad \ldots (12)$$

Accuracy for classification:

Accuracy=[True Positives (TP)+ True Negatives (TN)] / Total Samples … (13)

Precision and Recall:

Segmentation Result

The epoch-wise segmentation performance metrics, including training and validation losses and IoU values, are presented in Table 1.Visual segmentation results of the Swin UNet model by comparing input images, true masks, and predicted masks can be seen in Fig. 7, demonstrating its effectiveness in medical image segmentation. The segmentation performance across training epochs through IoU values, Dice coefficients, and loss curves for training and validation datasets are presented in Fig. 8. These results highlight the model's ability to improve segmentation accuracy and reduce loss as training progresses

F1-score trends demonstrate improvements in the balance between precision and recall. There is visualization of training and validation loss, highlighting model convergence over epochs in Fig. 9. For performance validation, the proposed framework was compared with VGG16, ResNet50, and DenseNet121 under identical training conditions. The Swin U-Net + EfficientNet-V2 model achieved 97.3% classification accuracy and 78.4% IoU, outperforming VGG16 (91.2%), ResNet50 (93.8%), and DenseNet121 (95.1%), confirming its superior efficiency over existing CNN-based approaches.

Classification Result

The epoch-wise performance metrics for classification, including training and validation losses,

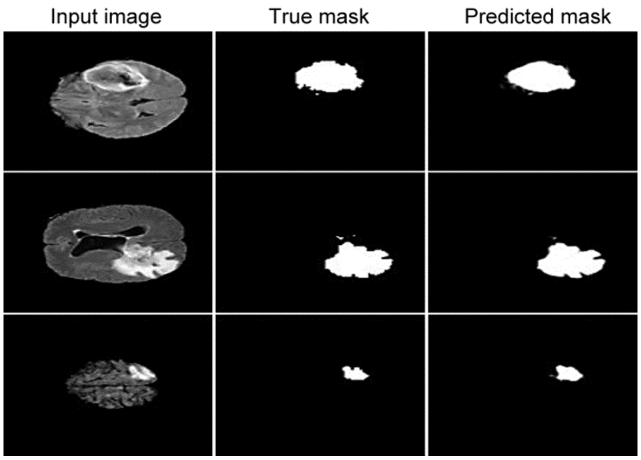

Fig. 7 — Visual segmentation results with Swin

accuracy, and the F1-score for the validation dataset, are summarized in Table 2.

There is depiction of the performance metrics of a classification model over training epochs in Fig. 9.

Precision=TP/[TP+FalsePositive (FP)],
Recall=TP/[TP+False Negatives (FN)] … (14)

F1 Score:
F_1=2. (Precision. Recall /Precision +Recall) … (15)

Comparative Analysis

The integrated model outperforms traditional methods and standalone DL architectures in segmentation and classification tasks. The combination of Swin Transformer-based hierarchical attention and EfficientNet V2's compound scaling improves accuracy, computational efficiency, and robustness. Comparisons with models such as ResNet50 and standard UNet demonstrate significant performance improvements.

A performance comparison of various methods, showcasing their segmentation IoU, Dice coefficient, classification accuracy, and F1-score, is provided in Table 3.

Discussion

Interpretation of Results

Empirical results validate the effectiveness of the proposed model in automating brain tumor diagnosis and improving clinical decision-making. Swin-UNet provides accurate tumor boundary segmentation, while EfficientNet V2 improves classification accuracy and addresses variability in traditional methods. Their integration creates a streamlined workflow that reduces reliance on manual processes and enhances diagnostic efficiency.

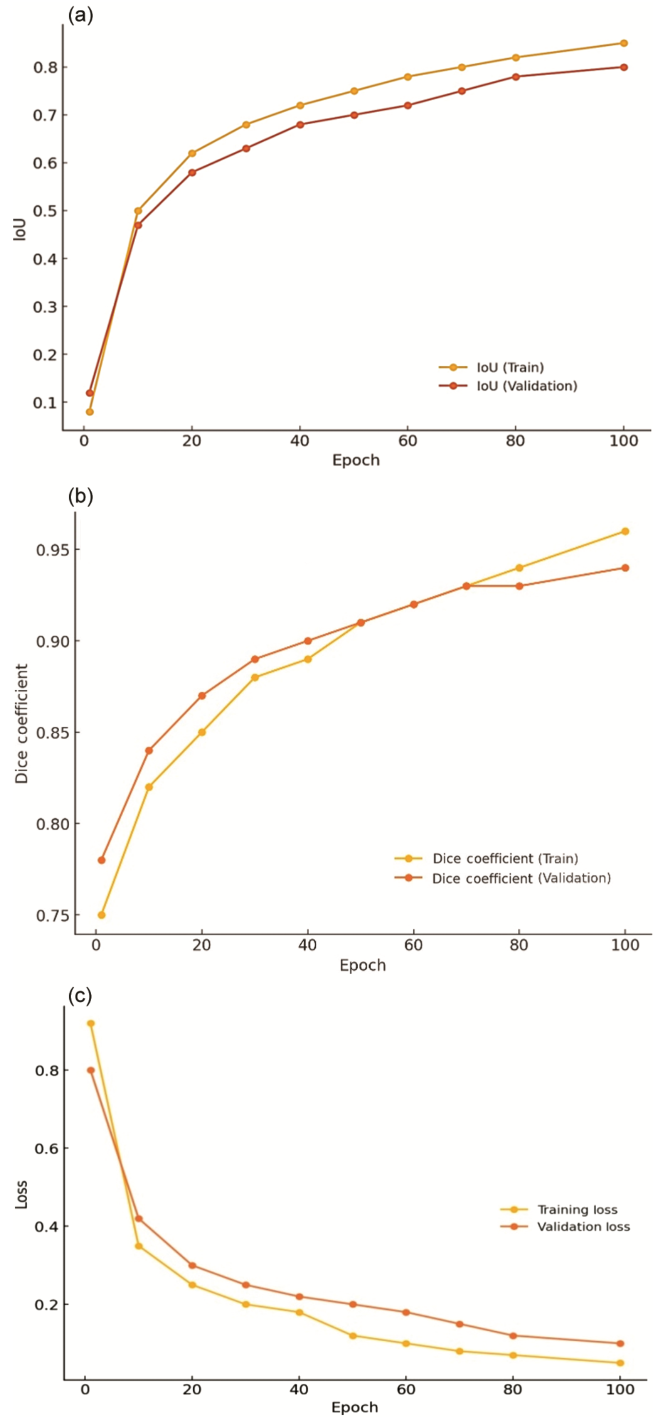

Fig. 8 — Performance metrics over epochs for segmentation: (a) IoU, (b) Dice coefficient, (c) Loss

IoMT's impact on brain tumor research

The IoMT advances medical research by enabling large-scale cloud-based validation of AI algorithms, ensuring models can handle variations in demographics, medical histories, and disease conditions for improved real-world performance. It

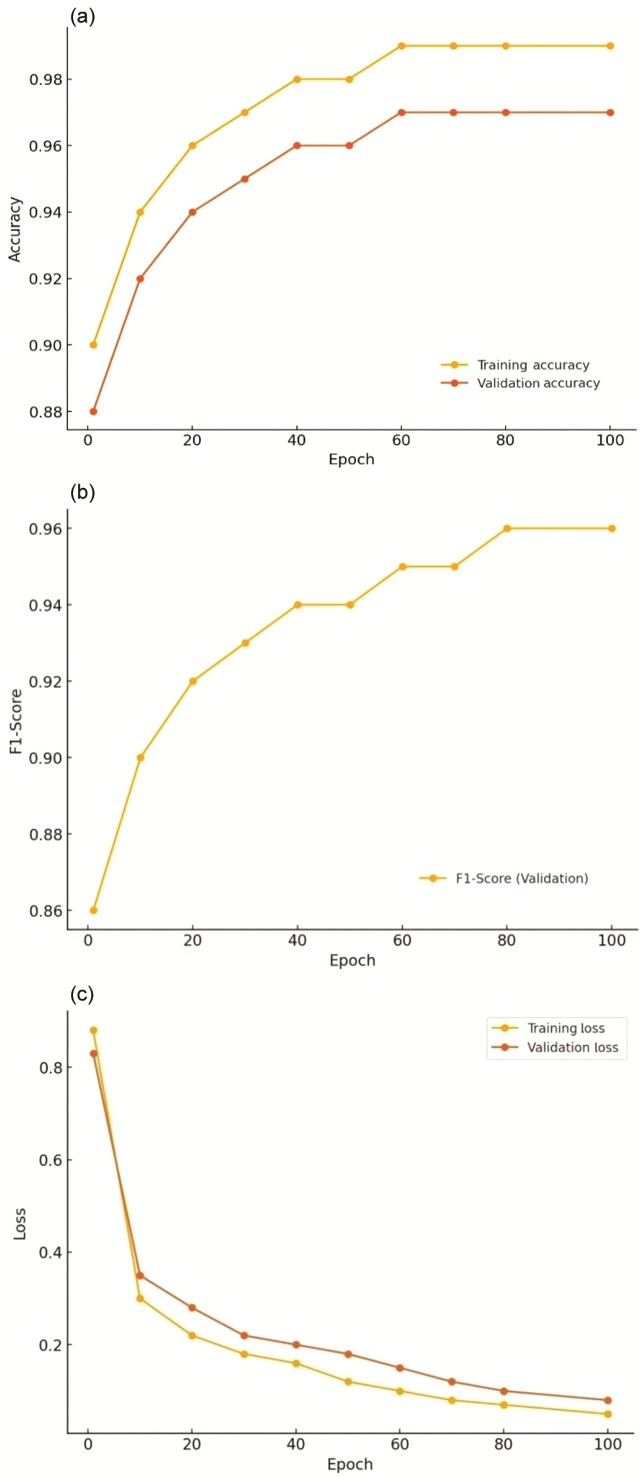

Fig. 9 — Performance metrics over epochs for segmentation: (a) Accuracy, (b) F1-Score, (c) Loss

also supports real-time monitoring of patient outcomes, providing continuous feedback to refine AI models and enhance diagnostic accuracy and clinical reliability. Additionally, IoMT enables the creation of large-scale datasets that support medical research, improve model development, and drive innovations in diagnostics and treatment planning.

Table 2 — Epoch-wise performance metrics for classification

Epoch	Training Loss	Validation Loss	Accuracy (Train)	Accuracy (Validation)	F1-Score (Validation)
1	0.88	0.83	0.90	0.88	0.86
10	0.30	0.35	0.94	0.92	0.90
20	0.22	0.28	0.96	0.94	0.92
30	0.18	0.22	0.97	0.95	0.93
40	0.16	0.20	0.98	0.96	0.94
50	0.12	0.18	0.98	0.96	0.94
60	0.10	0.15	0.99	0.97	0.95
70	0.08	0.12	0.99	0.97	0.95
80	0.07	0.10	0.99	0.97	0.96
100	0.05	0.08	0.99	0.97	0.96

Table 3 — Performance comparison with existing state-of-the art

Method (CitedPaper)	Segmentation IoU (%)	Dice Coefficient (%)	Classification Accuracy (%)	F1-Score (%)
DCT-CNN[1]	73	89	93	92
FCN[2]	75	91	95	94
U-Net[6]	73	89	93	92
DenseNet-201[7]	74	90	94	93
Optimized CNN[9]	72	88	92	91
Attention-UNet[15]	74	90	94	93
HSGNN-FLA[22]	—	—	99	—
ZFMBDPFRANet-DBO[23]	—	—	99	—
AViT-MRDNet+HB-RSO[24]	—	—	96	—
Proposed (IoMT-Swin UNet-EfficientNet)	78	93	97	96

Challenges in IoMT Deployment

Implementing IoMT in healthcare presents challenges related to data security, interoperability, latency, and adoption. Protecting sensitive patient information from unauthorized access and cyber threats is essential for maintaining trust and complying with regulations such as HIPAA and GDPR. Secure communication channels and strict medical device security standards are also necessary to reduce risks.

Another major challenge is interoperability among different medical devices and platforms, as variations in protocols and software compatibility can affect seamless communication. Processing large MRI datasets in real time also requires high computational power and efficient data transfer, making edge computing and optimized cloud infrastructure important for reducing latency. In addition, limited familiarity and reliability concerns among healthcare professionals can hinder IoMT adoption, highlighting the need for training programs, pilot studies, and demonstration of clinical benefits.

Limitations

Despite its strengths, the model faces challenges such as dependency on large annotated datasets and computational resource requirements. The approach may struggle with rare tumor types or imaging conditions not represented in the training data. Additionally, deployment of real-time clinical settings further requires validation and optimization.

Conclusions

The proposed integration of Swin-UNet and EfficientNet V2 achieves high performance in brain tumor segmentation and classification. By incorporating IoMT, the framework enables real-time data acquisition, processing, and remote diagnostics through connected healthcare devices. This IoMT-enabled approach provides an efficient and scalable diagnostic solution for healthcare environments. Future work will focus on integrating multimodal data such as CT and PET scans and validating the framework using larger datasets. The proposed model can support automated tumor detection, remote analysis, and clinical decision-making through IoMT-based healthcare systems. Future enhancements will include explainable AI, cloud-based integration, and multimodal learning to improve scalability and patient care.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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