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An IoMT enabled Deep Insight of MR Images for Brain Tumor Segmentation with Classification Using an Elevated UNet-RESNet Model

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Abstract: Brain tumors are a prominent cause of mortality on a global scale. The American Brain Tumor Association reports 90,000 primary brain tumor diagnoses annually, highlighting the need for improved diagnostic methods. Delaying brain tumor identification can result in significant financial costs and considerable suffering for patients. Timely identification of brain tumors is crucial for preserving both financial resources and human lives. Physicians's manual identification of brain tumors is quite challenging. Early and precise brain tumor detection is crucial to addressing these concerns. The incorporation of the Internet of Medical Things (IoMT) coupled with deep learning (DL) is essential for advancing contemporary healthcare solutions. The proposed work presents the IoMT-UNet-ResNet model, an advanced DL method designed specifically for accurately identifying and classifying brain tumors in MR image data. By harnessing the potential of the IoMT, the model effortlessly combines UNet for precise spatial delineation and ResNet-50 for sophisticated feature learning, resulting in outstanding accuracy. This model proves to be an invaluable asset for radiologists, as it simplifies and improves the precision of brain tumor analysis through the use of MRI data. The IoMT enables radiologists to effortlessly access and analyze diagnostic information in real-time, leading to enhanced patient care and results in the field of neuroimaging. The proposed IoMT-UNet-ResNet model outperforms by comparing and validating the existing technique.

Index Terms: Internet of Medical Things, Medical Image Analysis, UNet, Brain Tumor classification, Residual Network

1. Introduction

A tumor in the brain signifies an abnormal proliferation of cells within the cerebral region. These tumors can be benign or malignant, and they can start in the brain (primary) or spread throughout the body (metastatic) [1]. The brain is an intricate organ that performs cognitive activities, sensory processing, and motor control. It consists of billions of neurons and is responsible for regulating the body's functions, emotions, and thoughts. Manual detection of brain tumors is a challenging, time-consuming task that demands a high degree of expertise. Brain tumors are often detected through a combination of medical history evaluations, physical exams, and advanced imaging studies like MRI scans. Radiologists and other healthcare experts carefully examine these pictures to discover anomalies and traits that indicate a brain tumor. However, manual interpretation is prone to variability and human error, making automated, accurate solutions increasingly important.

To address these issues, contemporary research focuses on medical imaging powered by machine learning (ML) and deep learning (DL) techniques. These systems have the ability to swiftly examine enormous datasets, potentially enhancing diagnostic efficiency and accuracy [5].

DL is currently the dominant solution for complicated jobs, exploiting its power to automatically build task-specific picture features that transcend hand-crafted features. Deep convolutional networks excel in feature extraction. Based on their location, secondary tumors might have different tissue types. M.B. Sahaai et al. [8] demonstrated the system's efficiency in recognizing and segmenting a variety of brain tumors across many datasets with varying sizes, intensities, and locations. Incorporating deep convolutional networks using the U-type ResNet architecture has the potential to improve outcomes in tumor localization. Brain tumor segmentation involves identifying active, edematous, and necrotic tumor areas. A fully convolutional CNN extracts features from the entire picture and tiny parts during segmentation. The CNNbased ResNet50 framework efficiently identifies and classifies tumors in brain pictures, as well as detects early stages of cancer nodes [11].

The landscape of healthcare has undergone a significant transformation with the emergence of the Internet of Medical Things (IoMT), enabling real-time connectivity between medical devices and advanced data processing systems. The proposed work introduces the IoMT-UNet-ResNet model, presenting an innovative method for precise identification and classification of brain tumors through segmentation and categorization. Seamlessly integrating into the IoMT architecture, our model leverages UNet for meticulous spatial delineation and ResNet-50 for sophisticated feature learning. This integration allows for highly accurate, accessible, and timely diagnosis in clinical environments. This proposed work introduces the IoMT-UNet-ResNet model, aiming to advance medical image analysis and support individualized healthcare solutions. This research examines the IoMT-UNet-ResNet model's methodology, empirical findings, and implications for healthcare practices and individualized medical diagnoses.

1.1. Organization of the paper

The structure of the paper is as follows: Section 2 provides a comprehensive examination of relevant literature, while Section 3 proposes the suggested IoMT-UNet-ResNet model for the classification and segmentation of brain tumors. Section 4 performs a comprehensive examination of the findings, and the report finishes by delineating forthcoming avenues for research in Section 5.

2. Background Study and Contribution

The main priority in brain tumor disease is the rapid identification of brain tumors to enable fast and suitable therapy. The optimal treatment modality, whether it radiation, surgery, or chemotherapy, may be ascertained based on this data. Consequently, the chances of survival for a patient with a tumor infection might be significantly enhanced if the tumor is accurately identified during its first phases. To overcome the limitations of earlier proposed models, various ML and DL algorithms for brain tumor detection have evolved over the years. For brain tumor detection, S. Ahmad et al. [1] employed a combination of traditional classifiers and transfer learning-based DL approaches. Their findings are based on a labeled dataset that includes images of both normal and dysfunctional brains. Transfer learning is accomplished by the use of seven approaches, each of which is followed by five classical classifiers. The reported findings reveal that the best model attained an accuracy of 99.39%. In their proposed work, F. K. Shoushtari et al. [2] presented Deep-Net, a sophisticated deep neural network designed to accurately categorize glioblastoma tumors in MR images based on their semantic characteristics. The Deeplabv3+ model was utilized with pre-trained ResNet18 parameters. A Deshpande et al.

[3] used open-access datasets to classify brain tumors using Convolutional CNN, this work uses Discrete Cosine Transform and Convolutional Neural Network image fusion to differentiate tumor and non-tumor tissues in datasets. H. Li et al. [4] developed a comprehensive approach for segmenting brain tumors in a separate study, they utilized a modified UNet architecture as part of their method. The suggested network improves information flow using a unique up-skip connection between encoding and decoding. Each block also has an inception module to improve network learning and a cascade training method for successive brain tumor subregion segmentation. N. Ghassemi et al. [5] prooposed a pretraining method based on Generative Adversarial Networks (GANs) for classifying tumors in MR images. They show that their strategy achieves higher accuracy compared to other methods when evaluated using a 5-fold cross-validation on the dataset.

L. Duan et al. [6] suggested a fully convolutional network (FCN) that can regress the 3D dense deformation field in a single shot from a registered picture pair. The FCN is a unique multi-scale frame that captures complementary picture information and characterizes spatial connection between image pairs, allowing for exact regression and optimum registration of complicated deformations. S. Kumar developed Dolphin-SCA based Deep CNN [7], an enhanced DL mechanism for better classification accuracy and effectiveness. MRI images undergo pre-processing before segmentation. The segmentation approach utilizes a fuzzy deformable fusion model and Dolphin Echolocation-based Sine Cosine Algorithm (Dolphin-SCA). Rajaragavi et al. [9] introduced a DL method for effective brain tumor segmentation and classification. They proposed an optimized bidirectional ConvLSTM UNet with attention gate, using Squirrel search optimization for segmentation. Additionally, a Hybrid Deep ResNet and Inception Model were employed for categorization. The squirrel search optimizer mimics the organized movement and searching activity of southern flying squirrels. The UNet model's hyperparameters are tuned using the squirrel optimizer. UNet now has bidirectional attention modules for location and channel, enabling it to extract additional characteristic traits. The intricacy of brain tumour segmentation in multimodal brain MRI is the subject of this work, which is led by K. Bhima et al. The suggested approach integrates enhanced Fuzzy C-Means Clustering with marker-controlled Watershed methods, demonstrating exceptional performance. The effectiveness of tumour segmentation and identification is demonstrated by thorough assessment on both actual and benchmark datasets [10]. The proposed model by Ankitha G et al. focuses on brain tumor detection and classification using MRI images. Leveraging DL, specifically ResNet50 and Xception architectures, the proposed model achieved impressive accuracies of 98.02% and 98.32%, showcasing its efficacy [12]. J. Zhang et al. propose a ResUNet model that incorporates an attention mechanism. This is a comprehensive 2D network designed to segment brain tumors. The system achieves a precision of 71.9%, surpassing the performance of its comparable studies [13]. Kalaiselvi T et al. make a noteworthy contribution to the field of medical image processing by concentrating on the development of a completely automated system for detecting brain tumours. Their suggested approach utilises wavelet modifications and clustering algorithms to segment tumours in MRI brain images. The paper thoroughly examines many wavelet types, such as Haar, Daubechies, Coiflet, Morlet, and Symlet. The work, assessed using information from BRATS2012 and the whole brain atlas, displays exceptional performance in terms of both quantity and visual aesthetics [14]. S K Panda et al. highlights the need of promptly identifying potentially life-threatening brain tumors and cysts in order to enhance survival rates. conducts a comparison of several algorithms for the identification of brain tumors, utilising a model that has been built and evaluated using six distinct algorithms. The suggested model achieves good accuracy by utilising the Kaggle dataset, with a special focus on the Pituitary Tumours and No tumours classes. Logistic Regression is identified as the most efficient technique with a 99.6% accuracy, closely followed by Random Forests and SVM [15]. M Z Khalik et al. proposed work involves CNN and transfer learning models, achieving 98% accuracy with VGG16. Crucial for early detection and treatment of glioma, meningioma, and pituitary tumors, enhancing healthcare[16].

2.1. Challenges in brain tumor segmentation

Brain tumor segmentation faces challenges due to tumor heterogeneity, image noise, limited annotated data, varying resolutions, and the demand for consistent contrast enhancement. The imperative for automated segmentation arises from the complexity of manual delineation and the potential for human error in intricate medical imaging analyses.

2.2. Challenges in brain tumor classification

The imperative for automated brain tumor classification arises from the intricate challenges in handling tumor heterogeneity, limited annotated data, cross-modality variability, and the need for efficient integration into clinical workflows. Automation ensures precision, scalability, and timely diagnostics in the complex landscape of medical imaging.

2.3. The major research impact of the paper are listed as follows

- Through the novel real-time application of IoMT, brain tumor research is expedited, facilitating quicker assessments by doctors and experts.
- Streamlined process enhanced diagnostic processes expedite and enhance the precision of decision-making for medical practitioners and radiologists.
- Enhanced accuracy the incorporation of ResNet-50 and UNet enhances the precision of MRI-based tumors segmentation and classification, offering medical professionals a reliable option.
- The IoMT model allows users to quickly obtain brain tumors analyses at any time and from any location, hence improving accessibility for healthcare providers.

3. Proposed IoMT-UNet-ResNet Model

The IoMT-UNet-ResNet model is an advanced and innovative solution for the intricate task of segmenting and categorising brain tumors in the domain of the IoMT. This model integrates the UNet and ResNet deep learning architectures to proficiently assess medical imaging in IoMT scenarios. The UNet component possesses remarkable proficiency in gathering complicated spatial data, enabling precise delineation of tumors boundaries, commencing from the segmentation stage. The high-resolution segmentation allows for the precise identification of the intricate spatial distribution of tumors and facilitates advanced analysis. During the classification phase, the ResNet component assumes control and uses its deep residual learning architecture to extract hierarchical features that are essential for properly characterising tumors. The IoMT framework enhances the capabilities of the model by facilitating seamless integration with medical devices and data streams. We can get more accurate localization and classification with the IoMT-UNet-ResNet model because it combines UNet's detailed segmentation with ResNet's advanced feature learning. This comprehensive methodology signifies a notable progression in the examination of medical pictures inside the IoMT ecosystems. It has the capacity to enhance diagnostics and offer individualised therapy by detecting and characterising brain tumors.

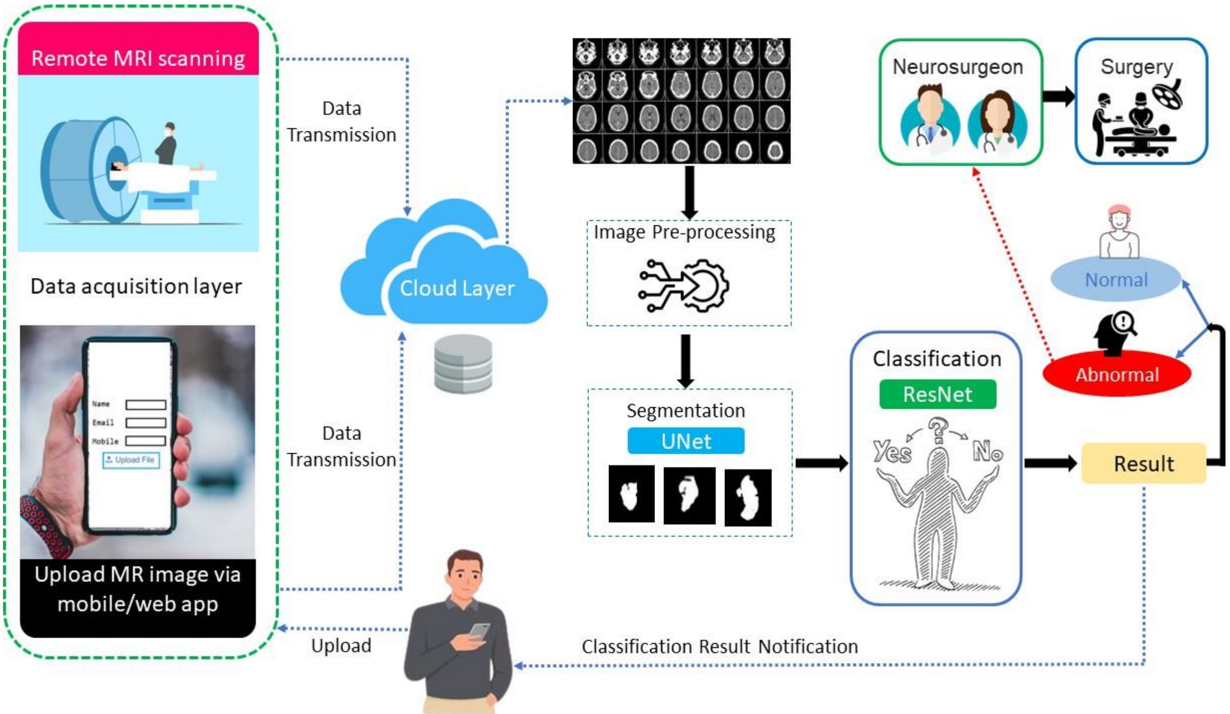

Fig. 1. Proposed Workflow Diagram: IoMT-UNet-ResNet for Brain Tumor Segmentation and Classification

3.1. IoMT based brain tumor classification

The term IoMT refers to a collection of healthcare apps and equipment that are interconnected over the internet. Remote monitoring and management of a patient's health are facilitated. It encompasses various gadgets such as wearables, health tracking applications, and so on. The objective is to enhance the healthcare standard by offering continuous monitoring of a patient's health, leading to expedited diagnosis and improved treatment. Detecting brain tumors at an early stage is a demanding and chaotic task. Various methodologies are being developed for the same purpose. However, the impact of these strategies will be amplified when integrated with the IoMT.
The Internet of Medical Things (IoMT) framework plays a crucial role in enabling real-time, secure, and remote diagnosis for brain tumor detection. In the proposed system, MRI data is captured via imaging devices and securely transmitted to the cloud using HTTPS and MQTT protocols. Data is encrypted with AES-256 standards to ensure confidentiality and integrity, and all communication channels comply with healthcare regulations such as HIPAA and GDPR.
The system is designed to operate in decentralized environments, allowing radiologists and clinicians to access patient scans from remote locations. Using edge-computing enabled IoMT gateways, preprocessing and anomaly detection can begin near the point of data acquisition before full analysis in the cloud. Additionally, the model supports automatic updates and remote diagnostics, ensuring the deployment remains current with evolving medical standards.
Integration with hospital systems such as PACS (Picture Archiving and Communication Systems) enables seamless data flow and storage. The IoMT infrastructure thus enhances accessibility, reduces diagnostic latency, and enables crossinstitutional collaboration for faster, more accurate diagnosis.

- **Data transsmission:** The combination of MRI and the IoMT enhances the detection of brain tumors by employing connection, instantaneous data transmission, and advanced analytics. Magnetic resonance (MR) images are easily sent over the IoMT for remote analysis by specialists.
- **Collaboration:** Enables collaboration among healthcare professionals, allowing specialists to review imaging results and contribute to the diagnostic process.

3.2. UNet based Brain Tumor Segmentation

Applying the UNet architecture, our method excels in accurately segmenting brain tumors from MR images. This approach enhances diagnostic precision, contributing to improved treatment planning. Convolutional neural networks (CNNs) with the UNet architecture were created for computer vision applications including semantic segmentation. The

U-shaped structure of the UNet architecture, with a contracting path and an expansive path after it, is what makes it unique. Convolutional and pooling layers, which collect hierarchical characteristics and decrease spatial dimensions, make up the contracting path. The expansive path creates segmentation masks and restores the spatial resolution using convolutional layers and upsampling. The feature that sets UNet apart is the presence of skip connections, which link equivalent layers in the expanding and contracting routes. The model can maintain fine-grained information when upsampling because of these skip connections. Its architecture makes it a potent tool for pixel-wise classification in a variety of applications by effectively balancing context and detail. By keeping a balance between context and detail, the U-shaped design is able to capture both global and local aspects in an efficient manner. The uses of UNet go beyond simple picture segmentation; in biomedical image analysis, it has shown to be very useful for tasks like organ segmentation in medical scans and cell segmentation in microscope images. Its broad use in many sectors where precise pixel-wise categorization is crucial is attributed to its adaptability, interpretability, and capacity to handle small amounts of training data. The popularity of UNet has also led to a lot of modifications and adaptations for particular use cases in the larger computer vision community.

Algorithm 1 IoMT-UNet-ResNet for Brain Tumor Segmentation and Classification

Step 1: Start
Step 2: IoMT Data Acquisition:
Use IoMT devices for MR image collection and securely transmit data to the cloud.
Step 3: Cloud Processing with UNet-ResNet:
Deploy UNet-ResNet model for brain tumor analysis and employ innovative preprocessing for image enhancement.
Step 4: Dynamic Segmentation:
Apply UNet dynamically for precise tumor segmentation and enhance accuracy with advanced segmentation techniques.
Step 5: Intelligent ResNet Classification:
Utilize ResNet for nuanced tumor classification and implement features for heightened classification precision.
Step 6: Smart Result Notifications:
Develop an intelligent system for timely result communication and ensure real-time channels for urgent cases.
Step 7: Continuous Learning:
Establish mechanisms for ongoing model refinement and adapt to evolving medical knowledge and technology.
Step 8: End

3.2.1 Architecture of UNet

The network is called UNet because it has a unique U-shaped structure, consisting of a contracting path (encoder) on the left and an expanding path (decoder) on the right. This distinctive design enhances comprehension of advanced characteristics and accurate positioning. The architecture comprises layers as seen in Fig 2.

- **The contracting path (encoder):** Convolutional layers and downsampling lower spatial dimensions and enhance feature channels in the contracting route. To introduce nonlinearity after each convolutional layer, a ReLU activation function is most often used.
- **Expandable path (decoder):** The expansive path entails upsampling the feature maps in order to restore spatial information lost during the contraction phase. This is often accomplished using transposed convolutions or upsampling layers. Following upsampling, convolutional layers are used to reduce the number of feature channels while increasing spatial resolution.
- **Skip connections:** Layers are connected between the contracting and growing paths using skip connections. These connections combine feature maps of the same spatial scale, which helps to preserve fine-grained information and allows for exact localization. They aid in minimizing the vanishing gradient problem during training and allow the network to access earlier, lower-level elements.
- **Last Layer:** A 1x1 convolution is commonly used in the final layer to translate the characteristics to the desired output classes. The last layer might employ different activation functions depending on the job (e.g., sigmoid for binary segmentation, softmax for multi-class segmentation).

3.2.2 Side-by-Side Comparison of Ground Truth and Predicted Mask in Brain MRI

Fig. 3 illustrates the integration of Brain MR images with Ground Truth annotations and Predicted Masks. This composite visualization showcases the alignment and disparities between manually annotated regions and algorithm-generated masks, providing valuable insights into the precision of the automated brain tumor segmentation system

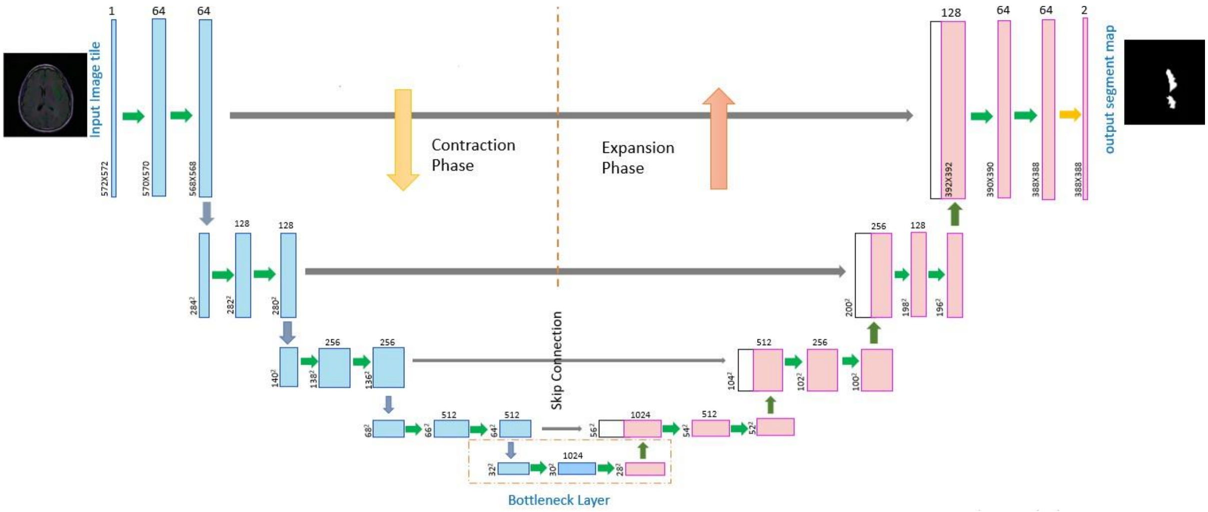

Fig. 2. Architecture of UNet

3.3. ResNet based Brain Tumor Classification

ResNet, also known as Residual Network, is a deep CNN architecture that addresses the vanishing gradient issue, which can hinder deep architecture learning. This makes deep neural network training easier. ResNet's major innovation is residual learning blocks, or residual units, which use shortcut connections to circumvent layers. These shortcut connections allow the model to learn the residual—the difference between input and output—of skipped levels, simplifying deep network training. Residual learning, which goes beyond standard designs, simplifies training extremely deep networks.Most ResNet topologies have numerous residual blocks with convolutional layers. These blocks may be stacked to create deep networks with good training. Residual connections allow information to flow straight throughout the network to avoid vanishing gradients and improve learning of low-level and high-level properties. ResNet has excelled in object detection, image segmentation, and image classification. eliminate polagarism. Due to its popularity, other ResNet variations have been created, including ResNet-50 and ResNet-101, which vary in complexity and number of layers. The ResNet architecture has grown to be a fundamental component of DL, impacting the creation of other neural network architectures.

3.3.1 Architecture of ResNet

ResNet-50 is a distinct iteration of the Residual Network framework including 50 layers. The architecture comprises a sequence of convolutional layers, residual blocks, and pooling layers. The primary innovation is the utilization of skip connections, also known as residual connections, which effectively mitigate the issue of the vanishing gradient problem. The design comprises convolutional layers with filters of size 1x1, 3x3, and occasionally 5x5, together with global average pooling and fully linked layers. The inclusion of skip connections enables the effective training of deep networks, hence enhancing their efficacy in many computer vision tasks. ResNet consists of the following layers as shown in Fig 4.:

- **Residual blocks:** The main breakthrough of ResNet lies in its utilization of residual blocks, which consist of skip connections that allow the network to learn residual functions by circumventing one or more layers. Residual blocks, rather than directly learning the intended underlying mapping from input to output, focus on learning the difference (residual) between the input and output of these blocks.
- **Deep Network Stacking:** ResNet allows for the stacking of a high number of layers, making it easier to train incredibly deep networks. The network's depth is accomplished by stacking residual blocks, which allows the learning of complicated hierarchical features.
- **Identity mapping and shortcut connections:** The skip connections as shown in Fig 4. in ResNet allow for the learning of identity mappings. If it is optimum for a particular layer, the network can learn to reduce the weights of certain layers to zero, enabling information to travel through them. These shortcut connections serve to eliminate the vanishing gradient problem, which occurs in very deep networks, making the training process more efficient. In mathematical terms, it would mean $y = x + F(x)$ where y is the final output of the layer.

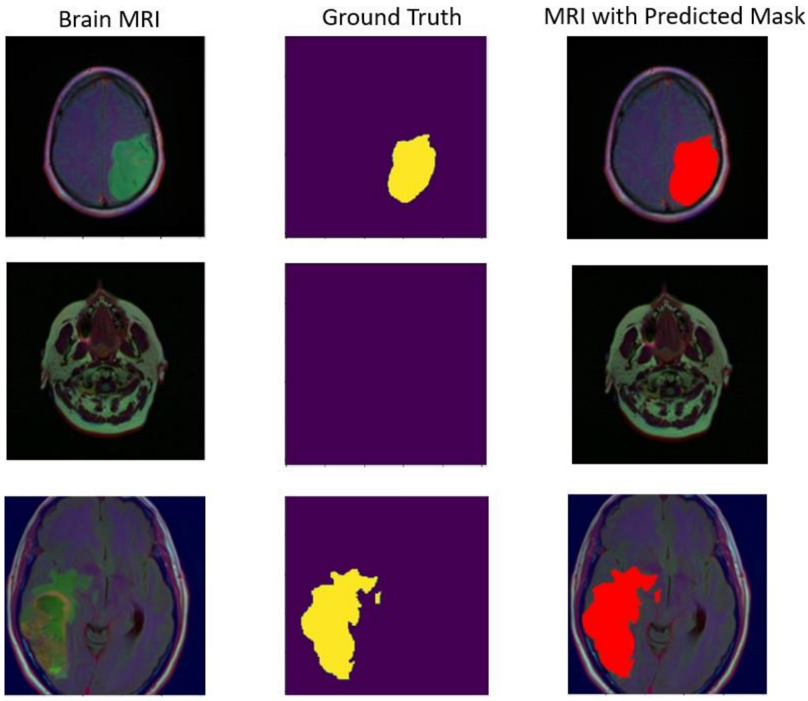

Fig. 3. Visual Assessment of Brain Tumor Segmentation: Ground Truth and Predicted Mask in MRI

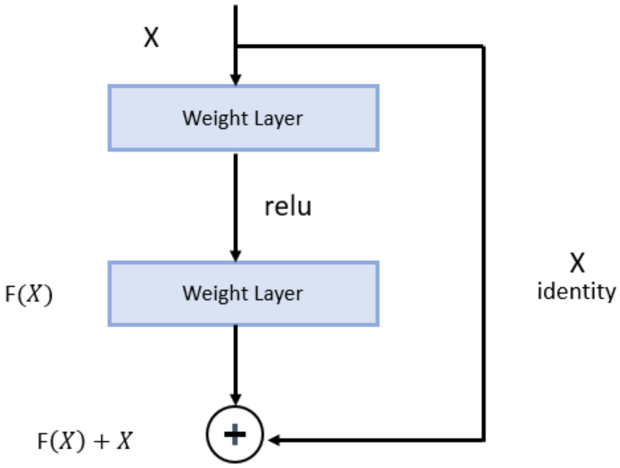

Fig. 4. Residual learning: a building block

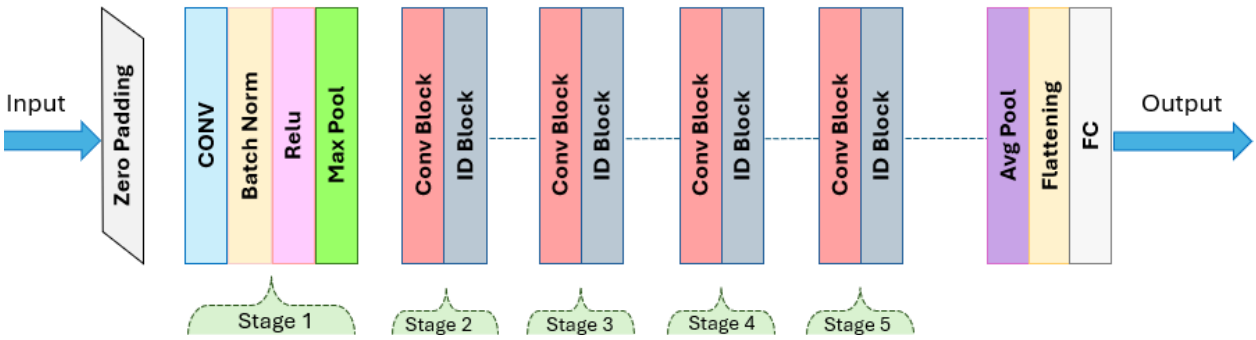

Fig. 5. Architecture of ResNet

- **Bottleneck Design (Deeper Variants):** Bottleneck blocks are used in more advanced ResNet models (for example, ResNet-50 and ResNet-101). These blocks are made up of a series of 1x1, 3x3, and 1x1 convolutions, which reduce computational complexity while preserving representational capacity.
- **Global Average Pooling and Output Layer:** ResNet is often completed with global average pooling, which calculates the average of each feature map and produces a fixed-size representation. To provide final output probabilities for tasks like image classification, a fully connected layer and a softmax activation function are frequently utilized.

3.4. Class-wise Analysis with MR Images: Classification Result Visualization

In Fig 6, titled 'Class-wise Analysis with MR Images: Classification Result Visualization,' we present a comprehensive visual examination of the model's classification outcomes. This figure highlights the incorporation of MR images, providing insights into class-wise analysis and enhancing the interpretability of our classification results

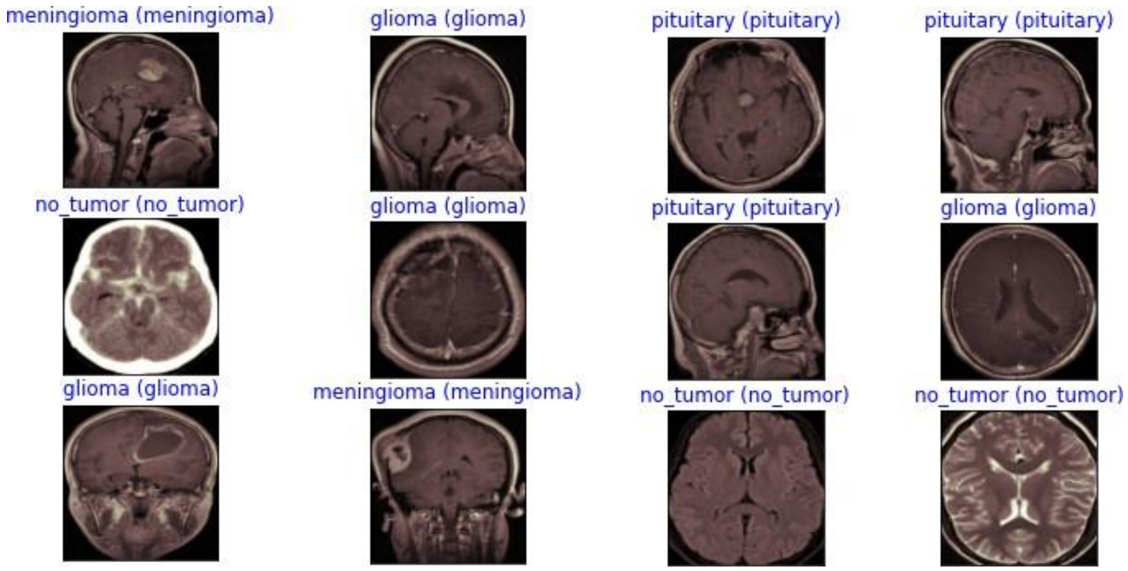

Fig. 6. Class-wise MR Image Analysis: Classification Outcomes

4. Result Analysis

The IoMT-UNet-ResNet model was thoroughly assessed during the Results Analysis phase, with an emphasis on important metrics including accuracy, loss, IoU (intersection over union), ROC (receiver operating characteristic) curves, and epoch-wise performance. A thorough analysis of the classification findings was given by the produced tables and confusion matrices. Together, these measures assist to measure the robustness of the model and identify possible areas for improvement in the segmentation and categorization of brain tumors.

4.1. Exploring the Dataset

The proposed work employed a comprehensive dataset from Kaggle.com for training and evaluating the IoMT-UNetResNet model in brain tumor segmentation and classification. The dataset comprises glioma, meningioma, pituitary, and no tumor categories, with balanced samples for training (1321, 1339, 1457, 1595) and testing (300, 306, 300, 405). This balanced distribution ensures a diverse representation for robust model evaluation.In our experiment, a conventional 80:20 data split allocates 80% for model training and 20% for performance evaluation.

Table 1 presents a comprehensive analysis of the dataset's composition, demonstrating how the samples are distributed across various classes during both the training and testing stages. This dataset design is intended to evaluate the performance of the IoMT-UNet-ResNet model for various brain diseases. It also enhances the reliability of our results. Also refer to Table 1 and Fig. 7 for specific details about the dataset.

Table 1. Dataset Description

Class	Training Samples	Testing Samples	Total Samples (%)
Glioma	1321	300	1621 (29.3%)
Meningioma	1339	306	1645 (29.7%)
Pituitary	1457	300	1757 (31.7%)
No tumor	1595	405	2000 (36.2%)
Total	**5712**	**1311**	**7023 (100%)**

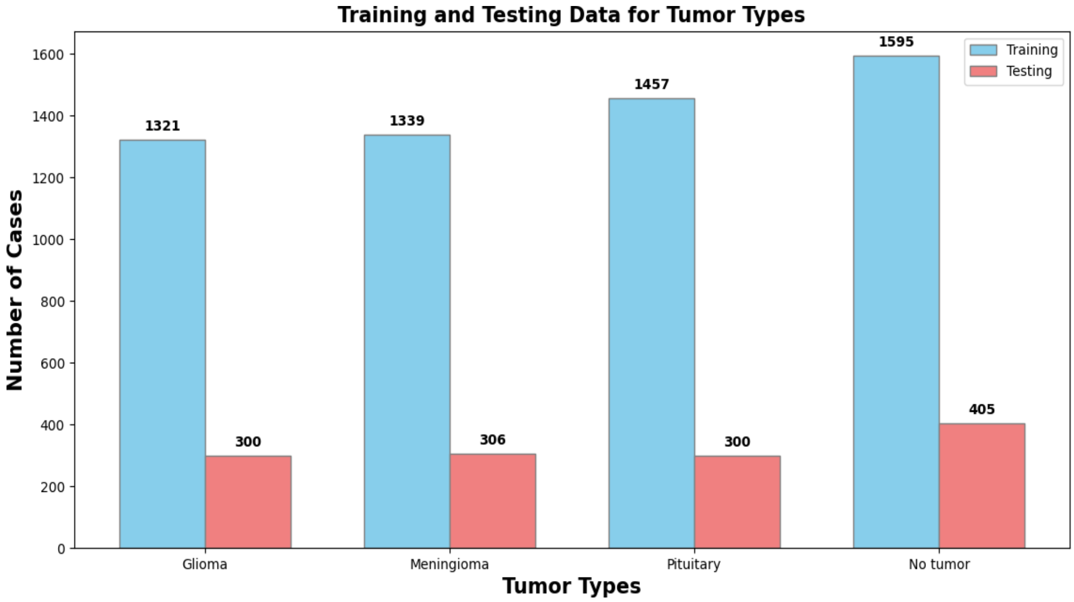

Fig. 7. Visualization of Dataset Distribution

4.2. Environmental Setup

We employed the Google Colab Pro+ platform, which is totally cloud-based, as our testing environment. We performed several experiments to evaluate the feasibility of our proposed methodology within the context of the IoMT healthcare system. The Google Colab Pro+ platform leverages an A100 Nvidia GPU for its computing operations. This platform utilizes a significant amount of RAM, namely 83.5 GB, and has a GPU runtime of 40GB. Utilizing a customized platform greatly improves the effectiveness and excellence of training DL models. The experiments were carried out utilizing Python version 3.9. The UNet and ResNet-50 models were constructed using Keras framework version 3, which functions as a high-level API. The backend used was Tensorflow version 2.15. The experiments were reproduced extensively to assure consistent outcomes. The results of the experiment were methodically documented and graphed.

4.3. Analyzing UNet Operational Efficiency

In this section, we conduct a thorough analysis of UNet's operational efficiency. Commencing with an epoch table detailing accuracy, loss, and IoU metrics, our evaluation progresses to visualizations illustrating the model's learning trajectory. The accuracy plot showcases improvement trends, while the loss curve indicates convergence. Finally, the IoU plot elucidates the model's proficiency in precise tumor segmentation, collectively providing a nuanced understanding of UNet's performance in brain tumor segmentation and classification.

4.3.1 Epoch-wise Analysis

The proposed work conducted on a per-epoch basis, as depicted in Table 2, offers a comprehensive overview of UNet's performance during the training process. The provided table presents accuracy, loss, and IoU metrics for each epoch, providing valuable information about the model's learning progress. This thorough assessment establishes a fundamental comprehension of UNet's operational effectiveness in the specific setting of brain tumor segmentation.

Table 2. Performance Metrics Summary for UNet Model over 50 Epochs (Represented in 10 Rows)

Epoch	Loss (Train)	Accuracy (Train)	IoU Train	Val Loss	Val Accuracy	Val IoU
1	0.92	0.98	0.07	0.79	0.99	0.17
5	0.38	0.99	0.50	0.43	0.99	0.45
10	0.27	0.99	0.62	0.41	0.99	0.47
15	0.23	0.996	0.67	0.29	0.995	0.59
20	0.18	0.996	0.73	0.26	0.996	0.63
25	0.15	0.997	0.76	0.25	0.996	0.64
30	0.14	0.9973	0.78	0.25	0.9957	0.64
35	0.13	0.9975	0.79	0.25	0.9957	0.64
40	0.11	0.9977	0.81	0.24	0.9957	0.65
45	0.11	0.9978	0.82	0.25	0.9958	0.65
50	0.10	0.998	0.83	0.24	0.9958	0.65

4.3.2 UNet Accuracy Plot

The accuracy plot of UNet, denoted as Acc, displays the model's performance over epochs, showcasing the proportion of correctly classified instances. Progressive patterns indicate improved learning ($\lim_{t\to\infty} \mathrm{Acc}(t) = 1$), whereas plateaus or fluctuations might indicate important training phases. This offers valuable insights into the model's accuracy advancement in brain tumor segmentation. As seen in Fig. 8.

4.3.3 UNet Loss Plot

The loss plot in UNet visualizes the model's performance over epochs, depicting the variation in the model's error (L) during training. The objective is to minimize the loss function, and descending trends indicate effective learning ($\min L$), while fluctuations or plateaus may signify pivotal phases in the model's optimization. This provides valuable insights into the loss dynamics (L_t) during brain tumor segmentation. As shown in Fig. 9.

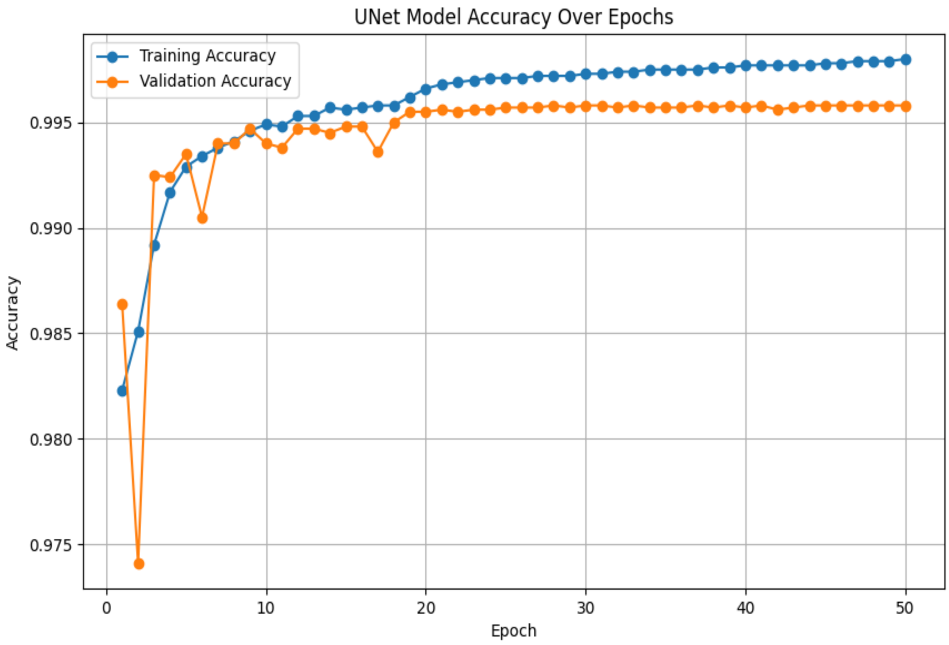

Fig. 8. Accuracy Plot

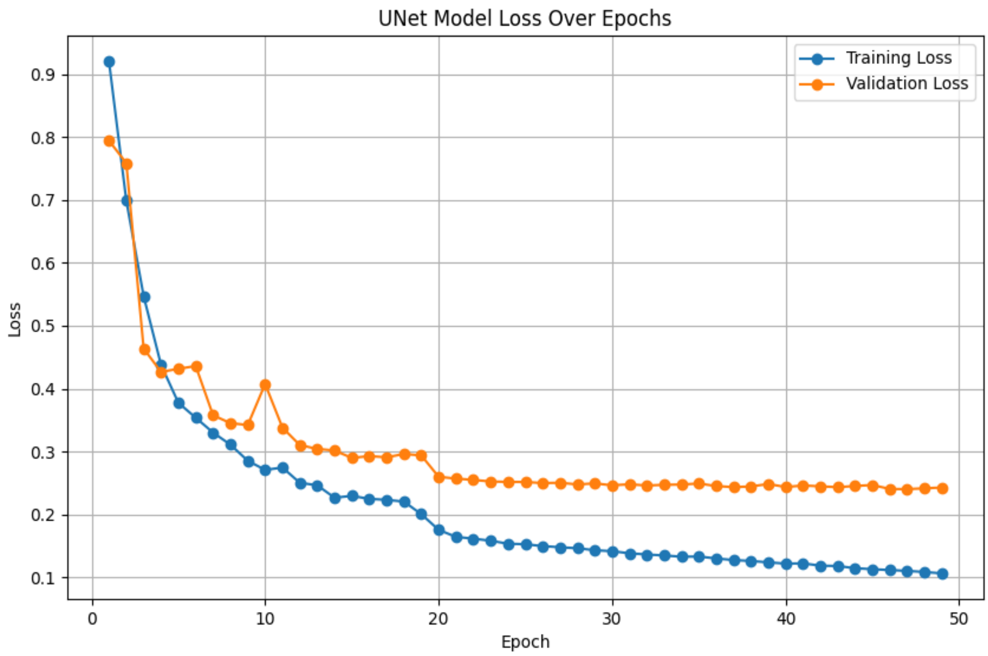

Fig. 9. Loss Plot

4.3.4 UNet IoU Plot

The IoU plot, representing Intersection over Union, quantifies the concordance between predicted and ground truth regions. Mathematically, it is expressed as $IoU = \frac{TP}{TP+FP+FN}$, where TP denotes true positive, FP signifies false positive, and FN represents false negative. Elevated IoU values, as illustrated in Fig. 10, signify improved accuracy in the segmentation of brain tumors.

4.4. Analyzing ResNet Operational Efficiency

4.4.1 Epoch-wise Analysis

The work used ResNet, a DL model, over 50 epochs to train and analyse brain tumors pictures, effectively capturing complex patterns. The performance of the model as it progresses through each epoch is meticulously recorded and displayed in Table 3, offering a thorough summary of its learning path.

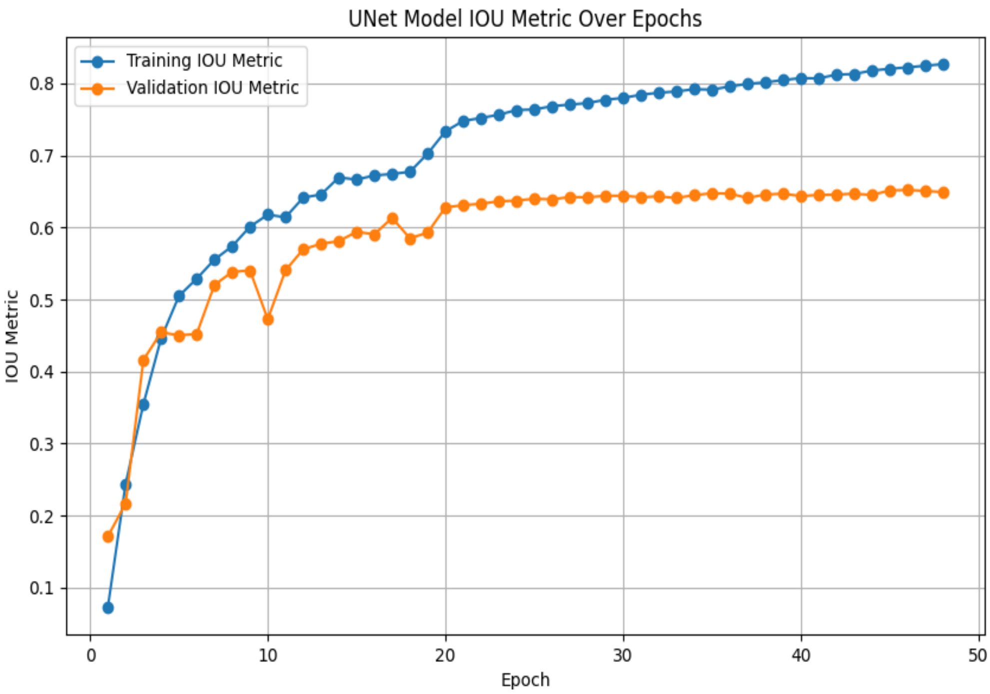

Fig. 10. IoU Plot

Table 3. Performance Metrics Summary for ResNet Model over 50 Epochs (Represented in 10 Rows)

Epoch	Loss (Training)	Accuracy (Training)	Loss (Validation)	Accuracy (Validation)
1	0.3368	0.8689	2.9624	0.2336
5	0.0366	0.9888	2.8430	0.2275
10	0.0035	0.9991	4.2281	0.4366
15	0.0027	0.9993	0.3016	0.9116
20	0.0034	0.9996	0.0374	0.9878
25	0.0030	0.9991	0.0393	0.9904
30	0.0032	0.9989	0.0396	0.9904
35	0.0030	0.9993	0.0395	0.9904
40	0.0039	0.9989	0.0396	0.9904
45	0.0019	0.9998	0.0391	0.9904
50	0.0034	0.9989	0.0397	0.9904

4.4.2 ResNet Accuracy Plot

The ResNet Accuracy Plot, presented in Fig. 11, provides a visual representation of the model's performance during training and validation. The ascending trajectory of both training and validation accuracy curves indicates the model's proficiency in correctly classifying brain tumor regions. This convergence suggests that the model effectively learns from the training data and generalizes well to new, unseen data, contributing to its robust performance.

4.4.3 ResNet Loss Plot

The ResNet Loss Plot, depicted in Fig. 12, portrays the dynamic evolution of the model's loss function during training epochs. Mathematically, Equation (1) calculates the loss as the discrepancy between predicted and actual values. The descending trend in the plot signifies the model's continuous refinement, minimizing errors and enhancing its capacity to accurately delineate brain tumor regions.

The loss function used in training the classification model is the Mean Squared Error (MSE), mathematically expressed as:

$$Loss = \frac{1}{N}\sum_{i=1}^{N}\left(y_i^{true} - y_i^{pred}\right)^2 \tag{1}$$

Here, N is the total number of data points, y_i^{true} is the actual label, and y_i^{pred} is the predicted output from the model. The MSE penalizes larger errors more severely, encouraging the model to reduce high variance between true and predicted values during training.

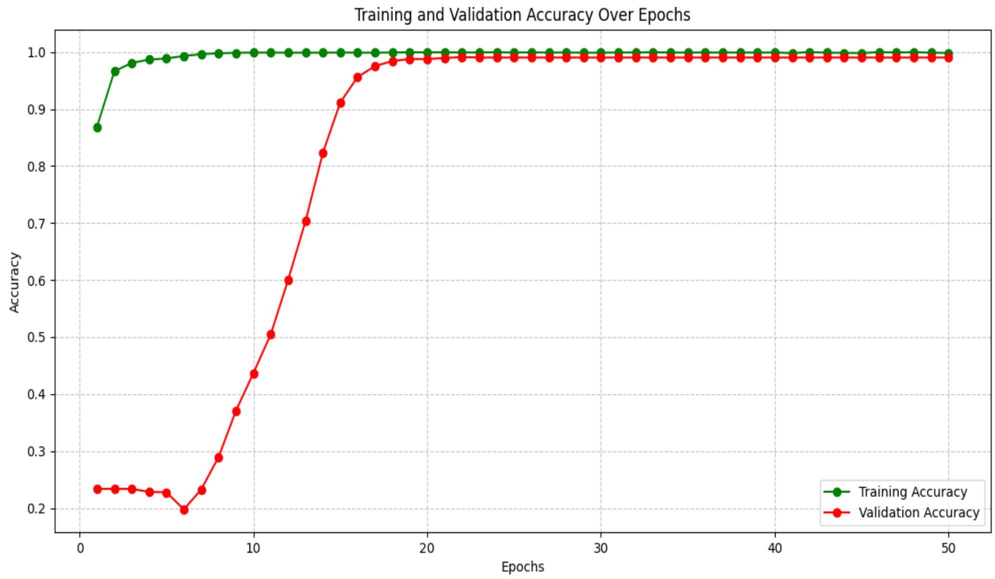

Fig. 11. Accuracy Plot

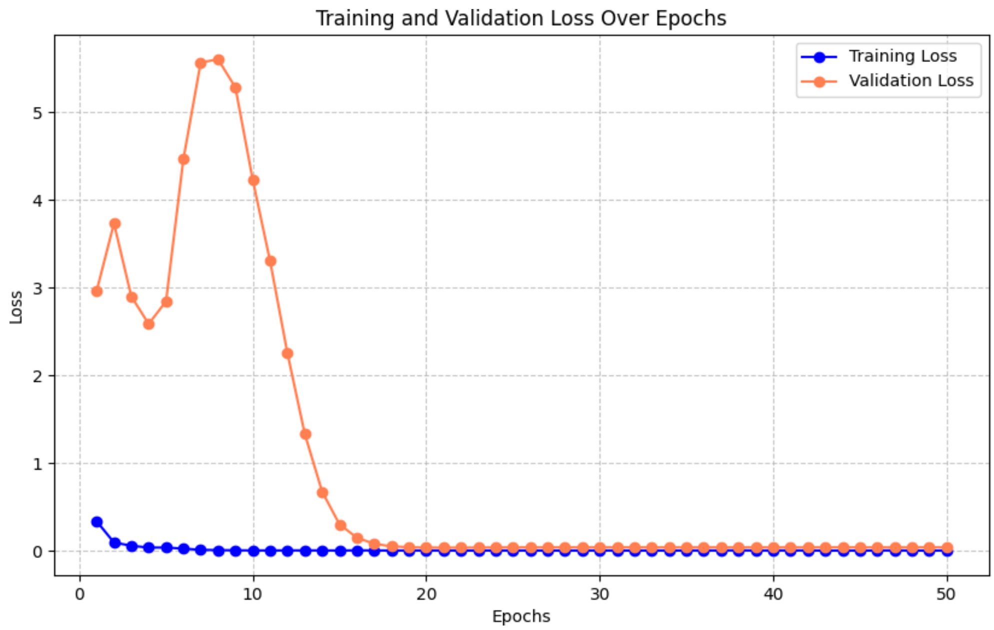

Fig. 12. Loss Plot

4.4.4 ResNet ROC Plot

The ResNet ROC Plot, depicted in Fig. 13, offers a detailed representation of the model's Receiver Operating Characteristic (ROC) performance. Mathematically, the ROC curve illustrates the trade-off between the true positive rate (Sensitivity) and false positive rate (1-Specificity) at various classification thresholds:

To evaluate classification performance, the True Positive Rate (TPR) and False Positive Rate (FPR) are computed as:

$$TPR = \frac{TP}{TP + FN} \quad (2)$$

$$FPR = \frac{FP}{FP + TN} \quad (3)$$

These metrics indicate how effectively the model identifies true positives while minimizing false alarms.

The shape of the ROC curve and its proximity to the top-left corner indicate the model's effectiveness in discriminating between brain tumor regions and non-tumor regions, showcasing its robust classification capabilities.

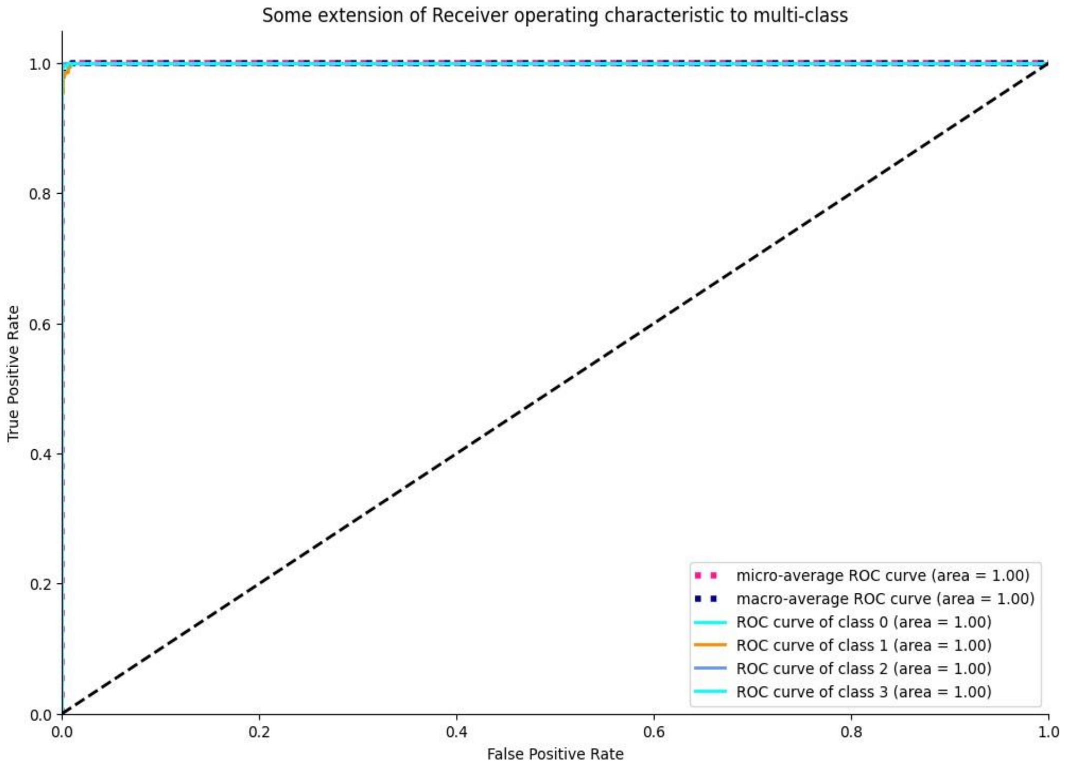

Fig. 13. ROC Plot

4.4.5 Confusion Matrix

The Confusion Matrix, depicted in Figure 14, provides a detailed breakdown of the ResNet model's performance, illustrating counts of TP (True Positives), TN (True Negatives), FP (False Positives), and FN (False Negatives). Mathematically, it is represented as:

$$\begin{matrix} TN & FP \\ FN & TP \end{matrix}$$

This tabular representation is essential for evaluating the accuracy and effectiveness of the model's classification. In Table 4, key metrics for model evaluation are outlined.

Accuracy:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

Accuracy gives the overall proportion of correctly predicted observations.

Precision:

$$Precision = \frac{TP}{TP + FP} \quad (5)$$

Precision quantifies how many of the predicted positives are truly correct.

Recall:

$$Recall = \frac{TP}{TP + FN} \tag{6}$$

Recall reflects the model's ability to identify all actual positive cases.

F1 Score:

$$F_1 = \frac{2 \,.\, Precision \,.\, Recall}{Precision + Recall} \tag{6}$$

The F1 score is the harmonic mean of precision and recall, balancing both concerns.

Table 4. Metrics for Each Class and Overall Metrics

Class	Precision	Recall	F1 Score
Pituitary	1.0	0.989	0.994
No Tumor	1.0	1.0	1.0
Meningioma	0.983	0.994	0.989
Glioma	0.992	0.983	0.987
Overall Metrics Accuracy		0.9917	

In our comparative analysis, as depicted in Table 5, the IoMOT-UNet-ResNet model for brain tumor detection and classification showcases exceptional accuracy and efficiency when compared with contemporary techniques in the field. This reinforces the potential of our model to significantly contribute to the advancement of medical image analysis and brain tumor diagnostics.

Table 5. Comparison of Proposed Model with Existing Techniques

References	Model	Accuracy (%)
S. Ahmad et al. [1]	DenseNet+SVM	98.83
F.K. Shoushtari et al. [2]	Deeplabv3+ A	97.53
L. Duan et al. [6]	GAN + ConvNet	95.6
M.B. Sahaai et al. [8]	ResNet	95.3
Ankitha G et al. [12]	ResNet50 and Xception	98.02 and 98.32
M Z Khaliket et al. [16]	VGG16	98
(Proposed)	IoMT-UNet-ResNet	99.17

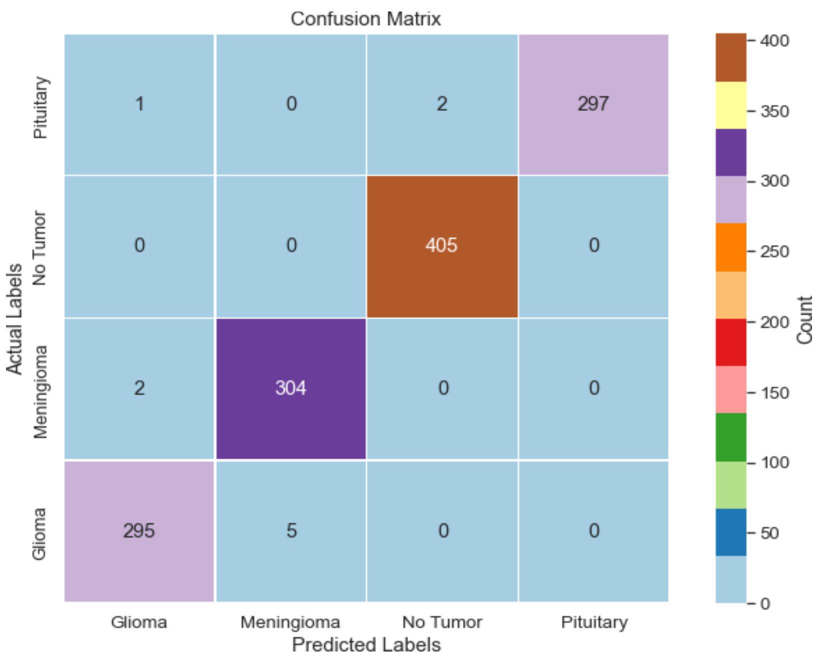

Fig. 14. Confusion Matrix

5. Discussion

In conclusion, the IoMT-UNet-ResNet model has demonstrated remarkable efficacy in the segmentation and classification of brain tumors, leveraging Kaggle MR datasets. The UNet segmentation and ResNet50 classification components exhibited exceptional precision and accuracy, particularly notable in the identification of Pituitary tumors. This research signifies a significant leap forward in automated neuroimaging diagnostics, holding promise for improving clinical decision support systems.

While the IoMT-UNet-ResNet model demonstrates high accuracy in classifying brain tumors, real-world clinical deployment involves several practical challenges. Integration into clinical workflows requires compatibility with existing hospital information systems (HIS) and imaging software (PACS/RIS). This necessitates standardized interfaces and interoperability protocols such as DICOM and HL7. Moreover, clinical settings demand models that are interpretable and auditable. The black-box nature of deep learning systems can limit their trustworthiness among clinicians. Therefore, explainable AI (XAI) components, such as saliency maps or attention heatmaps, should be incorporated to visually justify predictions to radiologists. From a regulatory standpoint, the model must undergo rigorous validation and certification processes by regulatory bodies such as the FDA or CE to ensure safety and efficacy. Additionally, training modules and user manuals need to be developed for healthcare personnel to interpret the AI results reliably. Deployment must also consider hardware infrastructure, network availability, and cyber-security. The system should be tested for latency, fault tolerance, and data loss in low-resource clinical environments. By addressing these considerations, the IoMT-UNetResNet framework can evolve from a research prototype into a deployable, trusted tool for modern neurodiagnostics.

Looking ahead, future research should prioritize expanding the model's capabilities and ensuring its robustness across diverse datasets. Collaborative efforts with healthcare professionals are crucial for validating the IoMT-UNet-ResNet model in real-world clinical settings. Moreover, addressing interpretability and ethical considerations will enhance the model's acceptance among medical professionals. The success of this model paves the way for continued advancements in automated brain tumor analysis.

In addition to brain tumor analysis, future work will focus on extending the model's capabilities to classify multiple diseases from MR images, such as brain cysts. This expansion into a broader range of pathologies demonstrates the potential of the IoMT-UNet-ResNet model to contribute significantly to the field of medical imaging and diagnosis. As technology and medical understanding evolve, ongoing research will play a pivotal role in refining this model for broader clinical applicability and addressing a wider spectrum of neurological conditions.

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