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Application of MobileNetV3 and U-Net Architectures in Deep Learning for Brain Tumor Detection

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Abstract—Brain tumors are neurological conditions that affect essential bodily functioning, necessitating a prompt and precise diagnosis. Brain tumors are frequently detected with magnetic resonance imaging (MRI), but manual interpretation is laborious and heavily reliant on radiologists' skill. Deep learning has become a popular method for improving medical image analysis. This paper suggests a hybrid deep learning architecture for MRI image based brain tumor identification that combines MobileNetV3 and U-Net. U-Net was utilized for tumor region segmentation, and MobileNetV3 was utilized for tumor categorization. A publicly available Kaggle Brain Tumor MRI dataset and the BraTS 2021 Dataset were used in the study. The accuracy, precision, recall, F1-score, confusion matrix, AUC-ROC, dice coefficient, and intersection over union (IoU) metrics were used to assess the model's performance. The MobileNetV3 model exhibited good precision, recall, and F1-score values along with 95% classification accuracy. Furthermore, outstanding classification performance was demonstrated by the AUC ROC values, which reached 0.99 and 1.00. The U-Net model received a Dice Coefficient of 0.9404, an IoU score of 0.8940, and a validation accuracy of 0.9936 for segmentation. For precise brain tumor detection and visualization on MRI images, the suggested hybrid architecture successfully integrates classification and segmentation tasks.

Keywords—Deep Learning, MobileNetV3 Architecture, U-Net Architecture, Brain Tumor Detection, Magnetic Resonance Imaging.

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I. INTRODUCTION

The development of Artificial Intelligence (AI) technology has greatly impacted various fields, particularly Data Science and Generative AI, enabling large-scale data processing. The advancement of AI has also expanded into many sectors of life, including healthcare and medical sciences, where this technology is used to support disease diagnosis, medical image analysis, and faster, more accurate clinical decision-making. As technology continues to evolve, industries are increasingly encouraged to implement technological capabilities in practical applications to solve existing problems [1]. One of the rapidly growing AI applications in the medical field is Computer Vision, especially for disease detection through medical imaging such as MRI, ultrasound, and CT scans [2].

Medical image processing plays an important role in modern medical practice, particularly in supporting disease diagnosis. Imaging technologies such as X-rays, MRI, CT scans, and ultrasound are widely used to identify abnormalities or disorders in the human body, including brain abnormalities that can be detected with MRI. However, the interpretation of these medical pictures heavily depends on the expertise of specialist physicians, which may lead to variations in diagnosis and potential errors. Therefore, AI based systems that assist in medical image interpretation are essential to increase the precision and effectiveness of diagnosis [3].

One of the most dangerous neurological conditions is brain tumors and have a significant influence on the quality of life of patients. According to recent statistics, approximately 300,000 new brain tumor cases are diagnosed worldwide each year. Based on the cells from which they originate, brain tumors can be categorized into multiple categories, where glioma (50–60% of cases) is the most typical and aggressive type, followed by meningioma (20–30% of cases), which is generally benign but still potentially dangerous, and pituitary adenoma (10–15% of cases), which affects the endocrine system [4]. Each tumor type has distinct characteristics and requires different medical treatment approaches [5].

MRI has become the primary modality for brain tumor diagnosis because of its ability to provide high resolution soft tissue imaging. The main issue addressed in this study is the prediction and diagnosis of brain tumors. Manual MRI interpretation by radiologists faces several significant challenges, including the need for specialized expertise, time consuming analysis, and difficulty distinguishing different tumor types [4]. Therefore, the use of deep learning technology has become a strategic solution to support the diagnostic process [2]. Using deep learning models, namely CNNs (Convolutional Neural Networks), medical data can be analyzed efficiently and accurately, thereby enabling early detection of abnormalities. CNN is one of the most widely used techniques for processing and detecting brain tumors from MRI images [6]

This study also employs additional architectures, namely MobileNetV3 and U-Net, for brain tumor classification and segmentation. MobileNetV3 is an advanced version of the MobileNet family designed to produce lightweight, efficient, and highly accurate models. This architecture combines Neural Architecture Search (NAS) techniques and hardware-aware optimization to achieve optimal performance with lower computational requirements compared to conventional CNN models [7]. This efficiency makes MobileNetV3 highly suitable for medical image processing applications that require fast, lightweight, and accurate models.

In addition to tumor classification, MRI image analysis also requires segmentation to identify tumor regions in greater detail, including their locations and sizes. Therefore, this study utilizes the U-Net architecture for brain tumor segmentation. A Convolutional Neural Network (CNN) architecture called U-Net was created especially for biomedical picture segmentation, enabling the model to capture detailed spatial information and produce precise segmentation results [8]. The main advantage of U-Net lies in its skip connection mechanism, which combines high resolution and low-resolution features, allowing the model to accurately detect object boundaries even when trained on limited medical datasets. The combination of MobileNetV3 for classification and U-Net for segmentation is expected to produce a brain tumor MRI analysis system capable not only of identifying tumor types but also of accurately mapping tumor regions. This approach provides a more comprehensive analysis compared to using classification or segmentation methods alone [9].

This study utilizes a brain MRI dataset comprising four tumor classification categories: glioma, meningioma, pituitary, and no tumor, sourced from the Kaggle platform for model training. The dataset is relevant to this research's objectives because it provides sufficient visual data to train CNN models for the automatic identification and classification of brain tumors. CNN models are specifically designed for image classification, object detection,

and segmentation tasks, making them highly effective for object recognition applications [6]. In addition, the BraTS 2021 Dataset is used in this study because it provides multimodal Magnetic Resonance Imaging (MRI) scans along with detailed tumor segmentation annotations, including tumor core, edema, and enhancing tumor regions. The BraTS dataset has become a benchmark in deep learning based brain tumor segmentation research due to its high-quality annotations verified by radiology experts and the availability of multiple MRI modalities, including T1, T1CE, T2, and FLAIR [10].

This study employs several evaluation criteria metrics, including accuracy, precision, recall, F1-score, and a confusion matrix. These evaluation metrics are crucial because they give a complete image illustrating the model's functionality, including how well it handles both eligible and unfit data, in addition to prediction accuracy [11], also Area Under the Curve Receiver Operating Characteristic (AUC ROC), and Dice Coefficient. Dice Coefficient is used to measure the similarity between segmentation results and ground truth in MRI images, while confusion matrices and AUC ROC are used to evaluate classification performance in distinguishing tumor and non-tumor images [12]. By combining these evaluation metrics, the proposed study is expected to produce an effective and accurate brain tumor detection model.

II. RELATED WORKS

A. Brain Tumor

Neurological conditions known as brain tumors are characterized by the unbridled proliferation of aberrant cells in brain tissue. These tumors can have a major impact on patients' quality of life and neurological function. They can be benign or malignant. Due to improvements in diagnostic technology and longer life expectancies, central nervous system cancers are becoming more common worldwide [13]. Primary tumors and secondary tumors are the two main classifications for brain cancers. While secondary brain tumors are caused by cancer spreading to the brain, primary brain cancers originate from cells in other organs. within the brain itself. Gliomas, meningiomas, and pituitary tumors are the most prevalent kinds of primary brain tumors [14].

About 78% of cases of malignant brain tumors in adults are gliomas, making them the most common type. Glial cells, such as astrocytes, oligodendroglial cells, and ependymal cells, serve as supportive cells in the brain and give rise to this tumor. Conversely, meningioma is the most prevalent benign intracranial tumor, accounting for 10–15% of all brain neoplasms; a tiny portion may develop into cancer. The meninges, which are membrane like structures that encircle the brain and spinal cord, are the source of this kind of tumor. After gliomas and meningiomas, pituitary tumors are also among the most prevalent intracranial tumors. Pituitary adenomas typically grow slowly and are benign 14. Even though various tumor forms frequently appear visually identical on MRI imaging, many differentiating features have been found [15].

Every year, the number of brain tumor cases worldwide keeps rising. Every year, about 300 people in Indonesia receive a brain tumor diagnosis. In addition to affecting adults, brain tumors can develop in children at a quite young age. Sadly, a lot of people tend to overlook the early signs of brain tumors [16].

Brain tumors can be found using a variety of medical imaging methods, such as magnetic resonance imaging (MRI) and computed tomography (CT) scans. MRI enables clearer visualization of the brain's hard and soft parts and provides more detailed picture information than CT scans [17]. For the diagnosis of brain tumors, doctors have historically relied on biopsy techniques and manual observation. However, manual diagnosis is prone to human error, and biopsies necessitate a lengthy laboratory analysis process, usually lasting 10 to 15 days. As a result, using deep learning models has emerged as a viable way to facilitate quicker and more precise diagnostic procedures [16] [18].

B. MobileNetV3

A Convolutional Neural Network (CNN) architecture called MobileNetV3 was created to generate models that are lightweight, effective, and require little processing power. To increase network efficiency while maintaining high accuracy across many computer vision applications, including image classification, this architecture is an advance over the previous version, MobileNetV2 [7].

In terms of structure, MobileNetV3 keeps the core ideas of MobileNetV2, such as depthwise separable convolutions and inverted residual blocks. Information flow and gradients can be effectively maintained throughout the network with this approach. Additionally, by eliminating nonlinear activation functions during the feature compression step, the linear bottleneck concept is used to preserve crucial information in the last layer of each block. MobileNetV3 is extremely effective for image processing jobs because of this method [19].

C. U-Net

One of the Convolutional Neural Network (CNN) architectures created especially for image segmentation tasks, especially in the area of medical imaging, is called U-Net. Due to its capacity to generate precise pixel level segmentation, this architecture, which was first shown by Olaf Ronneberger. in 2015 has become one of the most often used techniques in medical image segmentation. In order to identify anatomical features and anomalous areas, the U-Net maps each pixel in the input image into a particular class. Compared to traditional detection techniques, this pixel based segmentation approach is crucial for medical picture analysis [20].

U-Net's architectural design, which permits deep feature extraction while maintaining high-resolution spatial information, contributes to its effectiveness in medical imaging applications. The design is composed of two primary paths that form a symmetrical "U" shape: the expansive path (decoder) and the contracting path (encoder).

Additionally, U-Net is known to perform exceptionally well when dealing with sparse labeled data, which is a typical situation in medical datasets. Even with comparatively little training data, the interconnected encoder-decoder topology enables stable gradient flow and aids in the model's learning of hierarchical feature representations. Because of this feature, U-Net is especially well suited for medical applications, where annotated datasets are frequently scarce [20]

Due to its advantages in producing detailed and efficient segmentation results, U-Net has been widely applied in many medical imaging methods, such as CT, MRI, and X-rays, and microscopy images. The model has become one of the primary methods for segmenting tumors, organs, blood vessels, and other biological structures [21].

III. METHOD

A. Research Flow

The research pipeline that addresses the application of the U-Net and MobileNetV3 architectures for the identification of brain tumors in MRI images is depicted in Figure 1. Model performance evaluation, MRI preprocessing, and dataset collection are all part of the study technique.

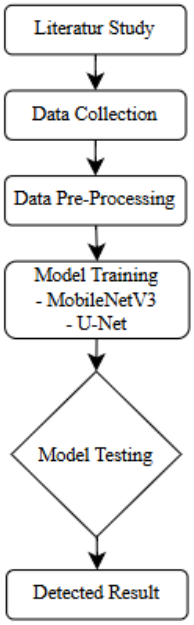

Figure 1. Research Flowchart

B. Data Collection

Brain Magnetic Resonance Imaging (MRI) images from publicly accessible online datasets via the Kaggle research dataset sharing platform comprise the data used in this study. This platform was chosen because it offers a variety of medical datasets that are frequently utilized in research on medical image processing and artificial intelligence.

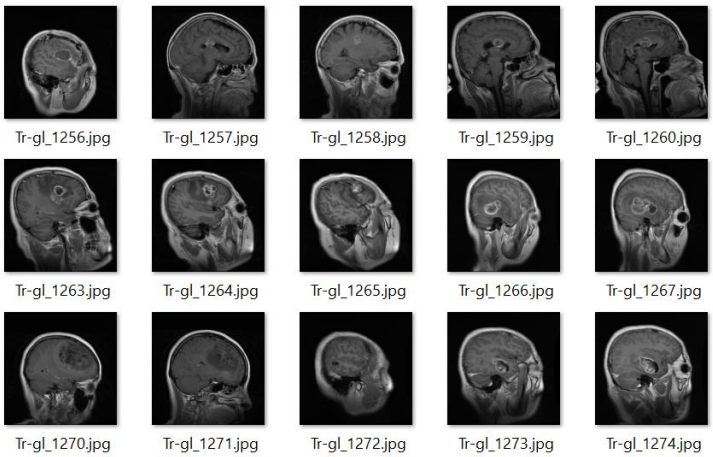

Figure 2. Brain Tumor MRI Dataset for Classification

According to the specifications of the brain tumor segmentation and classification procedures, this study makes use of two distinct datasets. Figure 2 shows the Brain Tumor MRI Dataset, it can be accessed using the Kaggle platform and is the first dataset utilized for brain tumor classification. The four types of brain MRI pictures in this collection are glioma, meningioma, pituitary tumor, and no tumor. The goal of integrating different dataset sources is to enhance the diversity of image attributes and improve the quantity of training data, which will help the deep learning model learn data patterns more efficiently and perform better in classification.

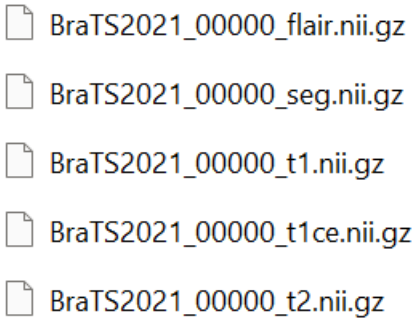

Figure 3. BraTS 2021 Dataset for Segmentation

Figure 3 shows that the BraTS 2021 Dataset is the second dataset utilized for tumor area segmentation. The BraTS dataset is among the most widely utilized benchmark datasets in deep learning based brain tumor segmentation research. This dataset contains multimodal MRI scans, including T1, T1 contrast (T1ce), T2, and FLAIR, each providing different information about brain tissue structures. In addition to MRI images, the BraTS dataset provides ground truth segmentation masks that detail tumor regions, including the tumor core, edema, and enhancing tumor areas. The compressed Neuroimaging Informatics Technology Initiative (NIfTI) format, which is often utilized in medical imaging datasets, is used to hold the BraTS 2021 dataset. Standard image viewers are unable to open .nii.gz files directly, in contrast to traditional image formats like .jpg or .png. With this method, the model can access volumetric MRI data and analyze medical images in greater depth.

C. Pre-Processing Data

Prior to being utilized in the model training procedure, MRI images were prepared during the data preprocessing stage. Enhancing data quality, standardizing image formats, and assisting the model in more accurately identifying brain tumor patterns were the goals of this phase. Color normalization, data scaling, data labeling, data splitting, and data augmentation were all part of this study's preprocessing procedure.

In order to normalize the pixel value distribution across all MRI pictures, color normalization was the initial step. In order to reduce variations in brightness and contrast between photos, pixel intensities were adjusted. Furthermore, every image was converted to RGB format. In order to guarantee that every image had a uniform format, color normalization was used, which improved the consistency of the model training process and decreased the likelihood of mistakes.

The following step was data resizing, which entailed transforming all MRI pictures into consistent dimensions in accordance with the model's input specifications. Each MRI image was given a segmentation mask annotation that indicated the tumor location during the data labeling phase. Labels in the form of mask images representing several tissue classes, including background, necrotic tumor, edema, and enhancing tumor, were previously provided by the segmentation dataset used in this investigation. The dataset's initial labels, which were 0, 1, 2, and 4, were changed to 0, 1, 2, and 3 in order to better fit the model training procedure and the employed loss function. This step's objective was to improve the model's ability to learn the distinctions between tumor tissue classifications.

Data augmentation was the last step, which sought to broaden the training data's diversity without creating fresh original photos. Several image changes, such as rotation, flipping, zooming, and shifting, were applied to carry out the augmentation procedure. To make the model more resilient to changes in MRI image orientation, rotation was used to randomly rotate the pictures. Additionally, shifting both horizontally and vertically was used to help the model identify tumor items even when their positions significantly

changed. It was anticipated that data augmentation would improve the model's generalization performance and lower the chance of overfitting during training.

III. RESULT AND DISCUSSION

These brain MRI scans with four classes: glioma, meningioma, pituitary, and non-tumor were used to test the MobileNetV3 architecture for brain tumor classification. Accuracy, precision, recall, F1-score, confusion matrix, and AUC-ROC measures were used to assess the model's performance.

A. MobileNetV3 Training Evaluation

The categorization of brain tumors is carried out using the MobileNetV3 architecture on brain MRI images, which are divided into four categories: glioma, meningioma, pituitary, and non-tumor. The model's performance is evaluated using metrics such as accuracy, precision, recall, F1-score, confusion matrix, and AUC-ROC to determine the model's ability to perform accurate classification.

Table 1. MobileNetV3 Evaluation Result

Tumor Type	Precision	Recall	F1-Score
Glioma	0.92	0.93	0.93
Meningioma	0.93	0.87	0.90
No Tumor	0.99	0.99	0.99
Pituitary	0.93	0.99	0.96
Accuracy			0.95
Macro avg	0.94	0.94	0.94
Weighted avg	0.95	0.95	0.95

According to Table 1 testing findings, the MobileNetV3 model's accuracy was 95%. This outcome shows that the model was able to accurately classify most MRI pictures. Furthermore, the precision, recall, and F1-score macro average and weighted average values were roughly 0.90, suggesting that the model's performance was quite steady and balanced across all classes with no discernible bias toward any particular category.

A more thorough examination of each class reveals that the notumor class performed the best, with precision, recall, and F1-score values of 0.99. These findings show that the model made very few classification errors in this class and was quite successful in identifying typical MRI pictures. The model obtained an F1-score of 0.93, a recall of 0.93, and a precision of 0.92 for the glioma class. Although some prediction errors still occurred in the form of false positives and false negatives, these figures show that the majority of glioma MRI pictures were accurately detected.

The model achieved a precision of 0.93, a recall of 0.87, and an F1-score of 0.90 for the meningioma class. Several meningioma photos were incorrectly identified and tended to be incorrectly placed into other categories, as indicated by the lower recall value when compared to the other classes. The visual similarities between meningioma and other tumor types in MRI images could be the reason for this. The pituitary class, on the other hand, performed comparatively well, with an F1-score of 0.96, recall of 0.99, and precision of 0.93.

All things considered, these findings show that the MobileNetV3 architecture offers strong classification performance for MRI based brain tumor identification. The model demonstrated significant generalization capabilities with consistent performance across all classes, even though the results were not as high as those of earlier studies. When compared to traditional CNN models, MobileNetV3's primary benefit is its great computational efficiency because of its lightweight construction, which allows it to achieve excellent classification performance. However, there are still difficulties in differentiating tumor

kinds with comparable visual features, especially in the meningioma class, which could be the subject of further study and advancement.

B. Confusion Matrix

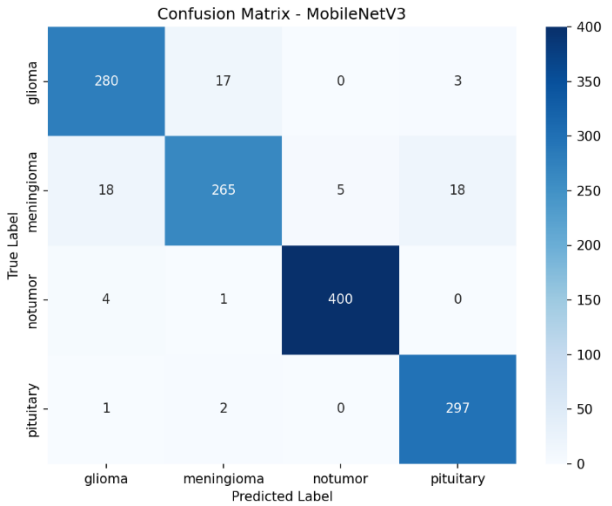

Figure 4. Confusion Matrix Visualization

According to Figure 4, which displays the confusion matrix results, the MobileNetV3 model successfully categorized most of the data. Of the 300 testing results in the glioma class, 280 were properly predicted. Nonetheless, several misclassifications persisted, with three data samples being projected as pituitary and seventeen data samples as meningioma. This suggests that some glioma MRI pictures have visual traits with other tumor forms, including meningioma.

In the meningioma class, 265 out of 306 testing data were correctly classified. Misclassification occurred in 18 data samples predicted as glioma, 5 as non-tumor, and 18 as pituitary. The comparatively higher number of errors in this class show that meningioma was the most difficult class for the model to distinguish compared to the other classes.

For the *pituitary* class, 297 out of 300 testing data were correctly predicted. The misclassification rate was very low, with only 1 data sample predicted as *glioma* and 2 as *meningioma*. This demonstrates that the model was also highly reliable in identifying pituitary tumors.

The glioma and meningioma classes had the greatest overall number of classification mistakes. This could be because these two tumor types have similar patterns and textures in MRI scans, which makes it harder for the model to correctly identify them. However, compared to the entire dataset, the number of prediction mistakes stayed quite low, which had no discernible impact on the model's overall performance.

C. Curve AUC ROC

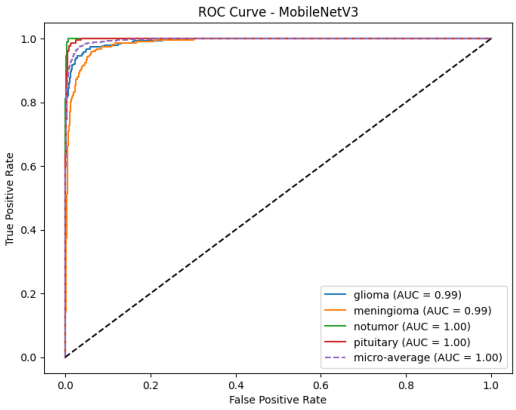

Figure 5. Curve AUC ROC

The MobileNetV3 model's AUC ROC curve shows outstanding ability in differentiating between each class of brain tumors. Each class had extremely high AUC values, with the glioma and meningioma classes reaching 0.99 and the notumor and pituitary classes reaching 1.00. Furthermore, the model's overall performance was extremely optimal, as indicated by the micro-average AUC value reaching 1.00.

The model attained a high True Positive Rate (TPR) and a low False Positive Rate (FPR), according to the ROC curves, which are situated close to the upper-left corner. This indicates that the model minimized mistakes in classifying negative samples while accurately identifying the majority of positive samples.

AUC values near 1.00 show that the model's ability to discriminate across classes is exceptional. Put another way, the model exhibits high sensitivity (the capacity to identify positive classes) and high specificity (the capacity to identify negative classes) in addition to producing accurate predictions.

The evaluation results utilizing the AUC ROC curve further support the MobileNetV3 architecture's high efficacy for MRI image based brain tumor classification. Even if a few classification errors still happened in some classes, the model's continuously high AUC values across all classes show that it can function dependably and consistently under a variety of data situations.

D. U-Net Training Evaluation

Tumor regions in brain magnetic resonance imaging (MRI) pictures were segmented using the U-Net architecture. In order to better identify aberrant spots in the MRI picture, the segmentation procedure attempts to pinpoint the position and shape of the tumor. Loss, Dice Coefficient, and Intersection over Union (IoU) were among the measures utilized to evaluate the model's effectiveness.

Table 2. U-Net Evaluation Result

Evaluation Matrix	Value
Dice Coefficient	0.9404
IoU	0.8940
Loss	0.0711
Validation Accuracy	0.9936

Table 2 displays a number of evaluation indicators based on the model training outcomes. A training dice coefficient of 0.9404 was attained by the model. A high degree of similarity between the model's segmentation output and the dataset's ground truth annotations is indicated by a Dice Coefficient value near 1. Furthermore, the model's training Intersection over Union (IoU) score was 0.8940. This finding shows that the

majority of the tumor locations in the MRI scans closely matched the tumor sites that the model predicted.

Additionally, the model's training loss of 0.0711 shows that it was successful in learning tumor segmentation patterns. Additionally, the validation accuracy was 0.9936, indicating that the model had good generalization capacity when processing unknown MRI images and was able to execute extremely accurate segmentation on validation data.

E. U-Net Segmentation

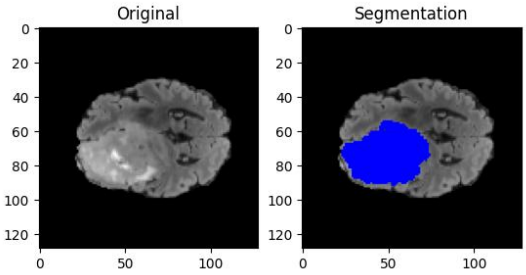

Figure 6. Segmentation Result

The segmentation visualization results are shown in Figure 6, which demonstrates that the U-Net model successfully identified tumor locations in brain MRI data. A blue segmentation mask was used to successfully emphasize the tumor location in the aberrant area of the image. The predicted tumor size was 1353.00 mm² based on the prediction results in figure 7. These results show that the model could help analyze tumor size from MRI images in addition to segmenting tumor locations.

The segmentation visualization further shows that the model was able to clearly detect aberrant brain tumor locations. The created segmentation mask more successfully supported visual interpretation of tumor location and size by closely matching the contour of the tumor area in the original MRI picture.

V. CONCLUSION

Using MRI scans, this study effectively created a hybrid deep learning architecture that combines MobileNetV3 and U-Net for brain tumor identification. While the AUC ROC findings demonstrated outstanding classification capabilities with AUC values ranging from 0.99 to 1.00, the MobileNetV3 model demonstrated good classification performance with 95% accuracy, high precision, recall, and F1-score values across all tumor classifications. With a Dice Coefficient of 0.9404, an IoU score of 0.8940, and a validation accuracy of 0.9936, the U-Net model showed good tumor segmentation performance. This was corroborated by visualization findings that correctly recognized tumor location and size. Although there were still a few misclassifications, especially between glioma and meningioma because of their comparable visual characteristics, the suggested hybrid design successfully combined classification and segmentation tasks to give a thorough brain tumor analysis. By using more datasets, sophisticated augmentation methods, and more intricate deep learning architectures, future research may enhance model performance.

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