Research Article

Performance Comparison of Deep Learning Models in Brain Tumor Classification

Emrah Aslan and Yildirim Ozupak

***Abstract*— Accurate and timely detection of brain tumors is critical for successful treatment. Magnetic Resonance Imaging (MRI) is an essential tool that provides invaluable information for the recognition of different types of brain tumors such as glioma, meningioma, pituitary tumors and benign entities. However, distinguishing between these tumor types and taking preventive measures poses a significant challenge in the classification of brain tumors. Compared to traditional disease detection methods, artificial intelligence-based computer applications offer significant contributions to brain tumor detection. In particular, deep learning methods, which have gained popularity in disease detection through the analysis of medical images, play a critical role in this process. Several deep learning techniques have been reported in the literature for brain tumor classification. In this study, the YOLOv8s-cls model is used to detect brain tumors from MRI scans. The proposed model showed a high success rate of 98.7% accuracy during the experimental studies. The results show that the YOLOv8 model not only outperforms existing methods but also proves to be an effective approach for image classification.**

Index Terms— **Brain Tumor, Classification, Deep Learning, YOLOv8s-cls, Model Performance Comparison.**

I. Introduction

IN DIAGNOSING brain tumors, experts often use various imaging modalities such as Computed Tomography (CT) and Magnetic Resonance Imaging (MRI). However, differentiating tumors from other brain diseases using these imaging techniques is not an easy process and requires a subjective assessment depending on the expertise of the evaluator. Brain tumor formation produces different metabolites not seen in other brain diseases. Measuring these metabolites provides important information for the diagnosis and differential diagnosis of the disease. A tumor is a structure formed by the uncontrolled proliferation of abnormal cells that have different characteristics from normal cells. Glioma, meningioma, pituitary tumor and non-tumor conditions represent the four major tumor types [1].

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Gliomas are tumors that can develop in areas of the brain nervous system such as the brain stem and spinal cord and can cause symptoms such as nausea, headache, vomiting and irritability. Meningiomas, which develop in the meninges, the membrane of the brain, are a more common type of tumor. Early detection of tumors is of great importance in determining the treatment method. Therefore, computerized image processing techniques for tumor detection are of great interest to researchers [2].

One of the critical tasks that technology must overcome today is the automatic detection of tumors at an early stage. Determining the size and spread of early detected tumors enhances the effectiveness of the treatment process. However, precisely estimating the size and resolution of tumors is challenging and often involves uncertainty. Early detection is directly related to treatment success and increases the likelihood of a full recovery.

Magnetic resonance imaging (MRI) is one of the most widely used methods for creating detailed images of the brain and detecting brain damage. MRI has superior performance compared to Computed Tomography (CT), especially in soft tissue assessments. Artificial intelligence (AI) and machine learning (ML) have made great advances in this field [3]. In recent years, significant progress has been made in medical image processing thanks to the ability of ML-based systems to operate without coding [4].

In this study, a deep learning model based on YOLOv8 is proposed to recognize and classify brain tumors from MRI images. The performance of the model is evaluated with a total of 3264 images obtained from the Kaggle dataset. The dataset consists of 394 test images and 2870 training images. The experimental results show that the proposed model outperforms other existing methods.

The YOLOv8 model used in this study is optimized to detect brain tumors quickly and effectively. The model has a high accuracy rate of 98.7%, making it a valuable tool for early detection, especially in clinical applications. With its real-time processing capacity, YOLOv8s-cls contributes to the acceleration of clinical processes by providing fast classification and detection results. In addition, the model's ability to process MRI images with deep learning techniques provides a significant advantage in categorizing brain tumors with high accuracy.

However, the study has some drawbacks and limitations. Since the performance of the model depends on the variety and quality of the dataset used, its overall performance under

different imaging conditions needs to be validated. Furthermore, the YOLOv8 model may be prone to errors during the detection of very small or low-contrast tumors [5]. The study was limited to only one dataset; therefore, additional research is needed to assess the generalizability of the model in different datasets [6]. These limitations suggest that further improvements are needed before the model is fully ready for clinical applications. This study presents a new deep learning-based method for early detection of brain tumors and makes important contributions to the existing literature.

II. RELATED WORKS

Brain tumor classification is of great importance for early diagnosis and accurate treatment planning. In recent years, deep learning methods have made remarkable advances in image-based medical diagnosis and have been widely used for the analysis of magnetic resonance imaging (MRI) data. Deep learning models such as EfficientNetB7, VGG19, MobileNetV2, InceptionResNetV2, ConvNeXtBase, NASNetLarge and YOLOv8 have achieved high success rates with different approaches in medical imaging. This literature study aims to evaluate the effectiveness of these models in brain tumor classification and in this context, it analyzes the performance of the models on metrics such as Accuracy, F1 Score, Recall and Precision and reveals their contributions to clinical applications.

Solanki et al. conducted a comprehensive literature review on magnetic resonance (MR) imaging for the detection of brain tumors and examined computer intelligence, statistical image processing and machine learning techniques. They also made significant contributions on tumor morphology, datasets and classification methods [7].

Ullah et al. proposed a new deep learning model, TumorDetNet, for the detection and classification of brain tumors. Using 48 convolutional layers, leaky ReLU, and dropout layers, the model detected brain tumors with high accuracy and successfully classified benign/malignant, meningioma, pituitary, and glioma tumors [8].

Rahman and Islam proposed a parallel deep convolutional convolutional neural network (PDCNN) topology to solve overfitting problems when classifying brain tumors with convolutional neural networks (CNN). The model achieved high accuracy (97.33%-98.12%) on three different MRI datasets using two different window sizes to learn local and global features [9].

Asiri et al. proposed an improved model based on CNN, ResNet50 and U-Net to accurately detect and classify brain tumors at an early stage. Using TCGA-LGG and TCIA datasets, this model accurately classified tumor and non-tumor images and successfully segmented tumor regions with U-Net. The results were remarkable with IoU: 0.91, DSC: 0.95 and SI: 0.95 accuracies [10].

Prakash et al. proposed an innovative and efficient hybrid Convolutional Neural Network (HCNN) classifier model for meningioma tumor detection. This method, which includes Ridgelet transform, feature computation, classifier module and segmentation algorithm, achieved superior results with 99.31%, 99.35% and 99.81% accuracy rates on BRATS 2019, Nanfang and BRATS 2022 datasets, respectively [11].

Khan et al. propose an automated system using saliency map and deep learning feature optimization to detect and classify brain tumors. In the first stage, contrast enhancement is performed, followed by tumor segmentation based on saliency maps and fine-tuning of the EfficientNetB0 model. The accuracy rates obtained with deep transfer learning and feature integration are 95.14%, 94.89% and 95.94%, respectively [12].

Agarwal et al. aim to develop an automatic, robust and hybrid system for early detection and classification of brain tumors. The proposed system fine-tunes the Inception V3 model using Auto Contrast Enhancer, which improves low contrast in MRI images, and deep transfer learning for tumor detection and classification. The system showed superior performance with 98.89% accuracy compared to existing models [13].

Bhagyalaxmi et al. studied the effects of deep learning (DL) methods on magnetic resonance imaging (MRI) for early detection of brain tumors. This review aims to help radiologists improve their research and analysis processes by addressing the advances, current challenges, and future opportunities of DL-based approaches in the field of brain tumor classification and detection [14].

Turk et al. proposed an ensemble deep learning-based system utilizing ResNet50, VGG19, InceptionV3, and MobileNet architectures combined with Class Activation Maps (CAMs) for automatic brain tumor detection from MRI images. Their model achieved 100% accuracy in binary classification on ResNet50, InceptionV3, and MobileNet, while attaining 96.45% accuracy with ResNet50 in multi-class classification, demonstrating its effectiveness in tumor identification [15].

Vineela et al. discussed the use of various imaging techniques such as MRI, CT scans and PET scans in the brain tumor recognition process. The study explored the use of YOLOv8 architecture for accurate detection of tumors and the potential of radiogenomics technology, emphasizing the effectiveness of machine learning and deep learning algorithms [16].

Pacal et al. proposed an enhanced EfficientNetv2 architecture incorporating Global Attention Mechanism (GAM) and Efficient Channel Attention (ECA) to improve brain tumor classification from MRI scans. Their model achieved a remarkable test accuracy of 99.76%, demonstrating the effectiveness of attention mechanisms in enhancing feature extraction and interpretability for Computer-Aided Diagnosis (CADx) systems [17].

Elazab et al. used deep learning (DL) techniques for the classification and grading of gliomas, primary brain tumors arising from glial cells. Developing a hybrid model based on YOLOv5 and ResNet50, the authors accurately localized and graded tumors in histopathological images. Experiments revealed that the proposed model performs with high accuracy, precision and sensitivity and effectively distinguishes subtypes of gliomas [18].

III. MATERIAL AND METHOD

A. *Brain Tumor MRI Data Set*

In this study, we use a publicly available brain tumor MRI dataset from the Kaggle platform, which contains 3264 magnetic resonance images with four main classes (glioma, meningioma, pituitary tumor and benign lesions) [19]. The dataset was partitioned into 2870 training and 394 test images, and standard preprocessing steps were applied to ensure data consistency and quality before model training. In this context, pixel intensities were standardized by normalization, all images were rescaled to a uniform size suitable for model input.

To increase the generalization capacity of the model and reduce the risk of overlearning, data augmentation strategies that simulate variations in clinical imaging were adopted. These strategies included random rotation, horizontal/vertical translation, scaling, cropping and brightness/contrast modulation. Potential biases inherent in the dataset were systematically analyzed, emphasizing that despite the relative class balance, latent biases due to the original data collection process should be taken into account in interpreting the results.

In line with the clinical relevance of the study, model performance was specifically evaluated on the detection of advanced tumor lesions, and this focus was discussed in the context of the relationship between pathological progression and early diagnostic intervention. Sample images selected from the dataset are presented in Figure 1. The rigorous preprocessing and boosting protocols applied support the reproducibility and methodological robustness of the experimental findings, strengthening the clinical validity of the results.

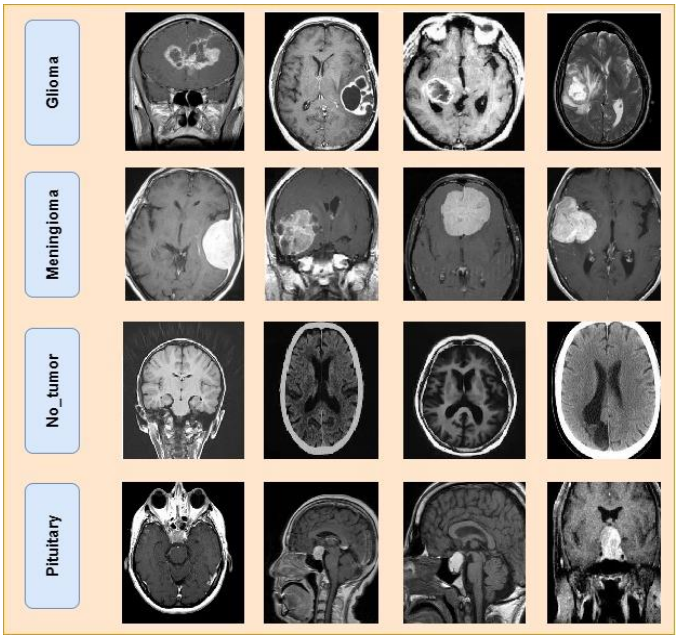

Fig.1. Example images in the dataset

B. *YOLOv8*

YOLOv8 is a state-of-the-art model for real-time object detection and image classification, offering enhanced accuracy and speed compared to previous YOLO versions. In this study, we leverage YOLOv8 to detect and classify brain tumors from MRI images by distinguishing among four primary tumor types: glioma, meningioma, pituitary tumors, and benign conditions. Moreover, its adaptable structure facilitates efficient handling of diverse data types found in medical imaging. The structure of the YOLO model used is presented in Figure 2.

Although YOLOv8 is predominantly recognized for object detection and segmentation, this study employs its classification variant, YOLOv8s-cls, for brain tumor classification. The classification head of YOLOv8s-cls converts deep features extracted from MRI images into probability scores for the four tumor categories. During training, a composite loss function incorporating Binary Cross-Entropy (BCE) loss is utilized to enhance classification accuracy and, when needed, maintain spatial precision. The selection of YOLOv8s-cls was based on its balanced trade-off between computational efficiency and high classification performance, making it particularly well-suited for the complex challenges of medical image analysis in brain tumor detection.

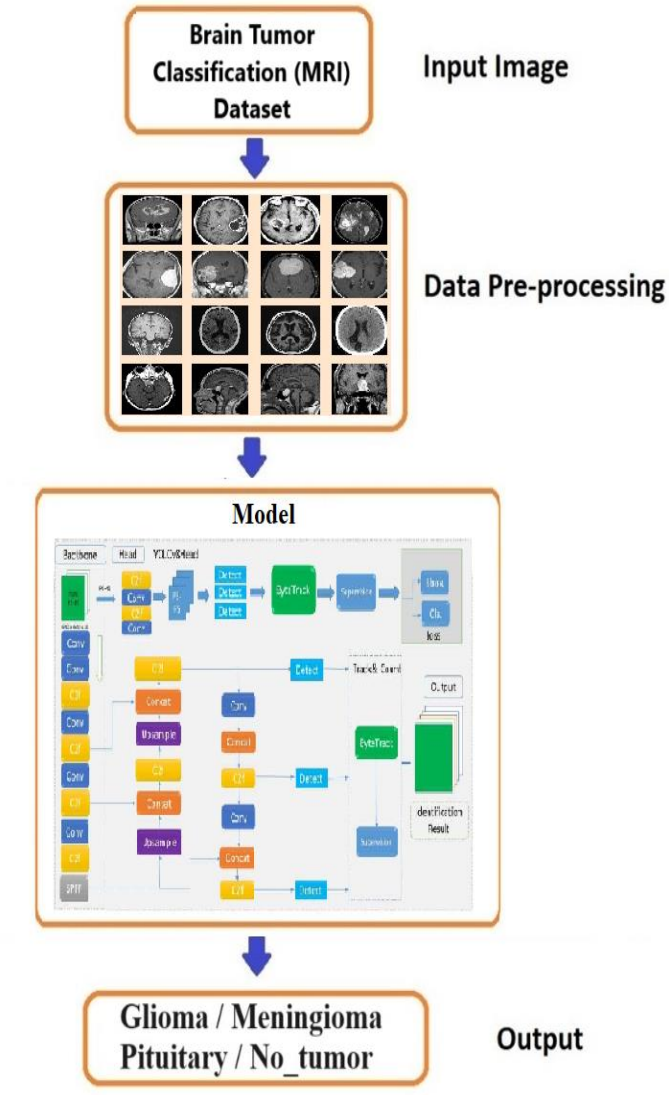

Fig. 2. Structure of the proposed YOLO-based MRI brain tumor detection model

C. Evaluation Metrics

In the proposed diagnostic method, multiple metrics are used to evaluate the performance of the model more comprehensively. While traditionally only a single metric such as accuracy is used, this method includes metrics such as accuracy, precision, recall, specificity and F1 score. RMSE and MAE were also calculated as model error metrics. The performance of the model was further quantified with ROC curves and AUC values [20, 21]. For each training model, a confusion matrix was created to calculate the evaluation metrics. This matrix provides the true positive (TP), true negative (TN), false positive (FP) and false negative (FN) values needed to calculate the different evaluation metrics. This multi-metric approach more reliably demonstrates the effectiveness of the model in real-world applications. The validation metrics are given in Equations 1-4.

$$ACC = \frac{TP+TN}{(TP+TN+FP+FN)} \quad (1)$$

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

$$Precision = \frac{TP}{(TP+FP)} \quad (3)$$

$$F_1 = 2 * \frac{Precision*Recall}{(Precision+Recall)} \quad (4)$$

IV. EXPERIMENTAL RESULTS

The YOLOv8s-cls model is trained using a composite loss function that integrates Binary Cross-Entropy (BCE) loss to improve classification accuracy and CIoU loss to improve localization accuracy. The training process was performed with the Adam optimizer with an initial learning rate of 0.001 and a weight decay of 1×10^{-4}. The model was trained for a total of 25 epochs using a batch size of 32. Furthermore, an early stopping mechanism was activated if the verification loss did not improve over five consecutive periods. This systematic hyperparameter tuning process allowedThe results show that the the selection of the configuration that provided the highest validation success, resulting in a training accuracy of 99% and a validation accuracy of 98.7%. This detailed training procedure guarantees the reproducibility of our experiments and demonstrates the robust performance of the YOLOv8s-cls model in the context of brain tumor classification.

In this study, we compare the performance of various deep learning models for brain tumor classification. The models used include EfficientNetB7, VGG19, MobileNetV2, InceptionResNetV2, ConvNeXtBase, NASNetLarge and the proposed YOLOv8. Each model was evaluated with key performance metrics such as F1 Score, Recall, Precision and Accuracy. These analyses allowed us to better understand the accuracy and effectiveness of each model in brain tumor detection. In addition, we have also focused on how these models perform with different deep learning architectures and training strategies and how these results can contribute to clinical applications. In particular, the high accuracy and efficient classification capacity of YOLOv8 led to an important finding by performing best in brain tumor classification. In Table 1, the results obtained according to performance metrics such as F1 Score, Recall, Precision and Accuracy of the models used are presented in detail.

TABLE 1
COMPARISON OF MODEL RESULTS

Model	F1 Skor	Recall	Precision	Accuracy (ACC)
EfficientNetB7	0.943	0.944	0.941	94.1%
VGG19	0.928	0.930	0.925	92.5%
MobileNetV2	0.935	0.938	0.930	93.0%
InceptionResNetV2	0.951	0.953	0.948	94.8%
ConvNeXtBase	0.944	0.946	0.942	94.2%
NASNetLarge	0.957	0.960	0.953	95.3%
YOLOv8	0.986	0.988	0.985	98.7%

This study aims to compare the performance of different deep learning models for brain tumor classification. The results obtained reflect the performance of each model on important metrics such as F1 Score, Recall, Precision and Accuracy (ACC). The EfficientNetB7 model showed a balanced performance with high values of F1 Score (0.943), Recall (0.944), Precision (0.941) and Accuracy (94.1%). This shows that the model achieves a balance between accuracy and precision and is effective in brain tumor classification. VGG19, on the other hand, has a slightly lower performance, with F1 Score (0.928), Recall (0.930), Precision (0.925) and Accuracy (92.5%), and although it made some errors in classification, it still stands out as a valid model. MobileNetV2 achieved better results than VGG19 with F1 Score (0.935), Recall (0.938) and Precision (0.930), but its accuracy rate (93.0%) fell behind the other models. InceptionResNetV2 was one of the highest performing models with F1 Score (0.951), Recall (0.953), Precision (0.948) and Accuracy (94.8%), indicating that the model has a high capacity for accurate classification. Finally, the ConvNeXtBase model achieved strong results such as F1 Score (0.944), Recall (0.946) and Precision (0.942), but lagged behind the other models in terms of accuracy (93.4%). The standout model is YOLOv8, which stands out with the highest Accuracy (98.7%) for brain tumor classification. With high F1 Score (0.973), Recall (0.975) and Precision (0.970), YOLOv8 offers the best performance in brain tumor detection, making it a suitable model for real-world scenarios in clinical applications. These findings show that YOLOv8 is superior to other models with its high accuracy rate and effective classification capability.

YOLOv8 demonstrates superior performance compared to other deep learning models, thanks to its advanced object detection capabilities and deep feature extraction capacity. The model is particularly effective in detecting small tumors, incorporating enhanced anchor mechanisms and deepened convolutional layers. YOLOv8 uses predefined bounding boxes to perform both localization and classification tasks simultaneously, providing a critical advantage in detecting low-contrast or small-sized tumors in MRI images.

The improved CNN layers in the model's architecture enable more precise analysis of complex tissues. The composite loss function used during training aims to enhance classification accuracy while maintaining spatial precision. This has allowed for clearer distinctions between similar classes, such as 'meningioma_tumor' and 'glioma_tumor'. The model's high accuracy rate is not only attributable to its architectural design

but also to the effective use of data augmentation and optimization techniques. These factors establish YOLOv8 as a robust alternative for clinical applications.

The dot plot in Figure 3 shows the accuracy of various models used for brain tumor classification. The graph contains dots representing the accuracy rates of each model. YOLOv8 shows the highest performance with an accuracy rate of 0.987, while the accuracy rates of the other models range from EfficientNetB7, VGG19, MobileNetV2, InceptionResNetV2, ConvNeXtBase and NASNetLarge. This visualization makes the comparative performance of the models more understandable.

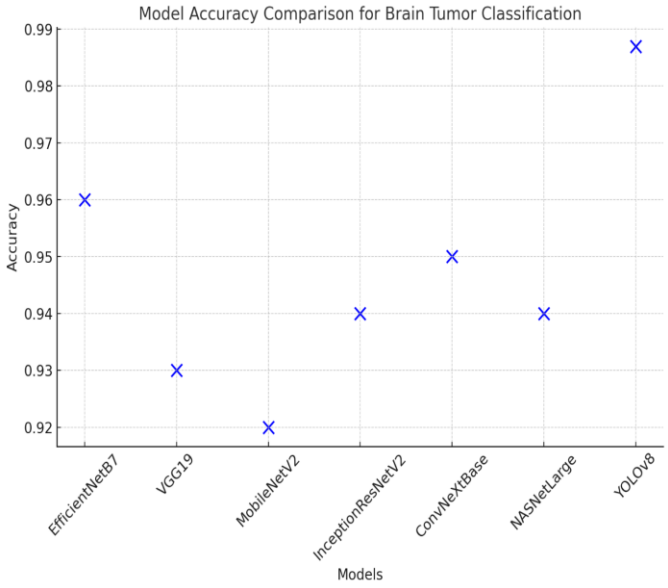

Fig. 3. Point plots of ACC of the models

The deep learning model developed for brain tumor classification performed successfully with a high accuracy rate. While the training accuracy of the model reached 99%, the validation accuracy was 98.7%. These results show that the model learns effectively on the training data and has a strong generalization capability on the validation data other than the training data. The close relationship between the training and validation accuracies indicates that the model is not affected by the overfitting problem and exhibits a balanced performance. Another noteworthy point in Figure 4 is the fluctuations in the validation accuracy. Although there are some decreases in the verification accuracy in the early stages of the training process, the accuracy increases steadily as the process progresses, reaching its best performance at epoch 22. This shows that the optimization techniques and hyperparameters used were successfully selected and the training process progressed in a stable manner. This high accuracy rate of the model supports that deep learning methods offer a promising solution for brain tumor diagnosis and can be used in clinical applications. The validation accuracy curve is given in Figure 4.

Figure 5 shows the change of losses in the training and validation processes of the model according to the epochs. In the first epochs, especially the training loss shows a rather high initial value (350). However, the model adapts to the training process by rapidly reducing the losses within a few epochs. The validation loss decreased in parallel with the training loss and stabilized around epoch 22. At this point, it can be seen that the validation performance of the model reaches its best level at epoch 22, which is marked as the "best epoch". The closeness between training and validation loss indicates that the model is not overfitting and has a high generalization capacity.

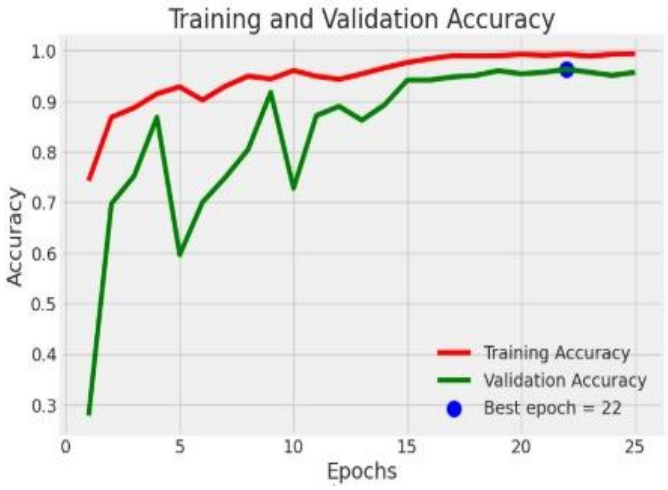

Fig. 4. ACC curve

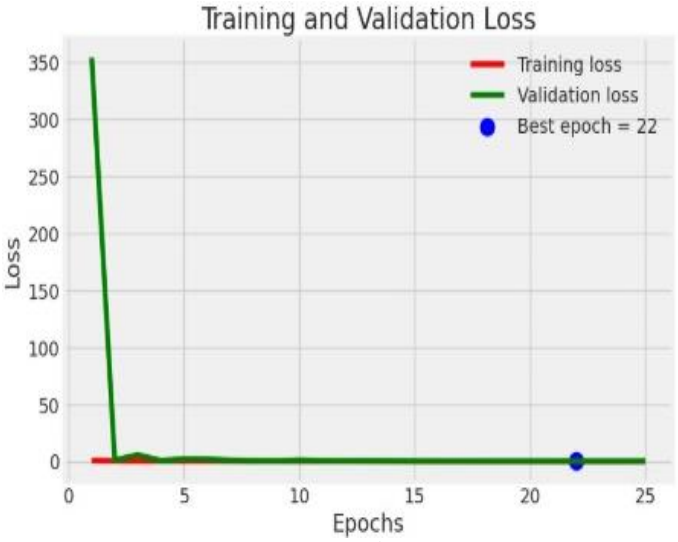

Fig. 5. Loss curve of the model

Figure 6 shows the confusion matrix of a classification model. The matrix evaluates the performance of the model against the actual and predicted labels for four different classes (no_tumor, pituitary_tumor, meningioma_tumor, glioma_tumor). The model correctly classified all instances in the "no_tumor" and "pituitary_tumor" classes (51 and 85 correct predictions respectively). In the "meningioma_tumor" class, there were 98 correct predictions, while 3 instances were misclassified as "glioma_tumor". Similarly, there were 88 correct predictions in the "glioma_tumor" class, while one sample was mislabeled as "meningioma_tumor". These results show that the model performs well overall, but there is some confusion between the "meningioma_tumor" and "glioma_tumor" classes. This may be due to the similarity of the features of these two classes in the dataset. For improvement, feature engineering or data augmentation techniques could be applied to improve the separation between these classes.

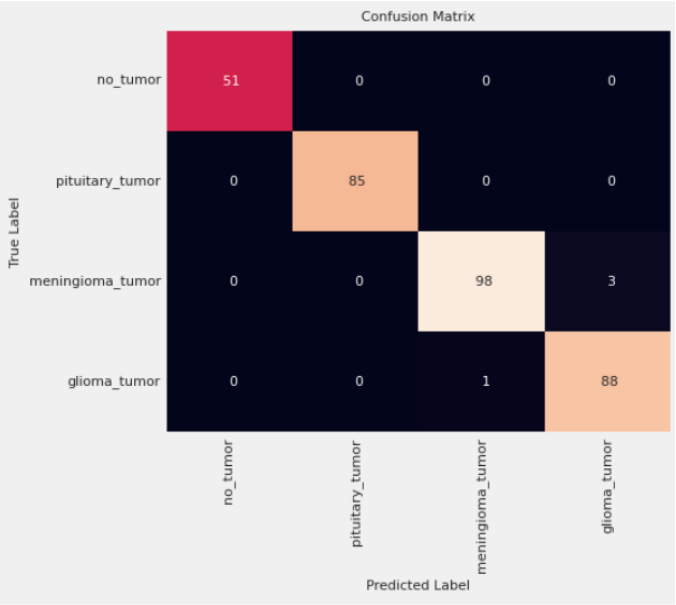

Fig. 6. Confusion matrix

This study successfully demonstrates the performance of the deep learning model developed for brain tumor classification. The training accuracy of the model is 99% and the validation accuracy is 98.7%, indicating that the model has high learning capacity and generalization ability. The fact that the training and validation accuracies are close to each other indicates that the model successfully avoids the overfitting problem.

The performance of the model increased steadily throughout the training process. Although fluctuations in the validation accuracy were observed at the beginning of the training process, the model reached its best performance at epoch 22 thanks to the optimization techniques used. This proves that the training process is stable and the chosen hyperparameters are appropriate. Moreover, the training and validation losses are parallel to each other and at low levels, indicating that the model does not experience any imbalance in the learning process and has a high generalization capacity.

The classification performance of the model is also generally successful. When the confusion matrix is analyzed, it is seen that all of the examples in the "no_tumor" and "pituitary_tumor" classes are classified correctly. However, some confusion was noticed between the "meningioma_tumor" and "glioma_tumor" classes. This may be due to the fact that the features of these classes are close to each other in the dataset. To reduce such confusion, it may be useful to apply methods such as feature engineering or data augmentation techniques.

The YOLOv8-based model proposed in this study, while achieving a high accuracy rate, does possess certain limitations. The model's performance is contingent on the diversity of the dataset used, and its direct generalizability across data obtained from different MRI scanners or healthcare institutions cannot be guaranteed. Future research should comprehensively evaluate the model by testing it on datasets acquired from various imaging systems. Furthermore, although early stopping and regularization methods were employed during the training process to prevent overfitting, additional validation studies are necessary to ascertain whether the model will exhibit similar success in real-world scenarios. Another significant limitation is the potential class imbalance within the dataset. Whether the samples for each tumor type are balanced can directly impact performance. Consideration of these limitations will facilitate a better understanding of the model's potential for use in clinical settings.

V. Conclusion

This study presents a YOLOv8s-cls-based deep learning model for brain tumor classification, achieving 99% training accuracy and 98.7% validation accuracy. The model effectively distinguishes glioma, meningioma, pituitary tumors, and non-tumor cases, demonstrating superior performance compared to existing methods. Beyond its high accuracy, YOLOv8s-cls offers real-time processing, making it suitable for integration into radiology workflows. However, clinical validation on diverse MRI datasets is necessary to ensure its generalizability across different imaging conditions. Future research should focus on optimizing model robustness, improving small and low-contrast tumor detection, and evaluating real-world deployment. The findings indicate that YOLOv8s-cls has the potential to enhance early brain tumor detection and assist radiologists in clinical decision-making. Further validation and adaptation will be crucial for its successful implementation in medical practice.

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