JOURNAL OF INFORMATICS DEVELOPMENT

E-ISSN : 2963-0568, P-ISSN : 2963-055X
Available online at:
https://ejournal.itbwigalumajang.ac.id/index.php/jid

Implementation of Deep Learning-Based YOLOv8 for Brain Tumor Detection in MRI Images

M Dzul Arsyl Majid[1], Achmad Firman Choiri[2], Cahyasari Kartika Murni[3]

Department of Information Technology, Faculty of Engineering and Informatics, Institut Teknologi dan Bisnis Widya Gama Lumajang, Indonesia[1,2,3]

Corresponding Author: M Dzul Arsyl Majid (idzularsylmadjid@gmail.com)

ARTICLE INFO

Date of entry:
10 February 2026
Revision Date:
4 April 2026
Date Received:
24 April 2026

ABSTRACT

Brain tumors are a condition with a high mortality rate that requires accurate early detection to support the medical diagnostic process. The goal of this project is to create a model that uses the You Only Look Once version 8 nano (YOLOv8n) algorithm to identify and locate brain cancers in Magnetic Resonance Imaging (MRI) scans and to evaluate its effectiveness using actual clinical data. This study employs an experimental method with a quantitative approach through the following stages: dataset collection, bounding box annotation, image preprocessing, data augmentation, model training, performance evaluation, and implementation in a simple web application. The dataset consists of 5,015 MRI images, comprising 5,000 public data points and 15 hospital clinical data points as external test data. Model evaluation was conducted using the precision, recall, mAP@50, and mAP@50–95 metrics. The YOLOv8n model's precision was 96.99%, recall was 94.37%, mAP@50 was 97.75%, and mAP@50–95 was 72.01%, according to the results. Testing on external data showed that the model was capable of detecting tumors in images that had not been previously trained on. These results indicate that YOLOv8n has the potential to be developed as an artificial intelligence-based early diagnosis support system for brain MRI images.

Keywords: Brain Tumor, *Computer Vision, Deep Learning, O*bject Detection, *YOLOv8*.

Cite this as: Majid, M. D. A., Choiri, A. F., & Murni, C. K. (2026). Implementation of Deep Learning-Based YOLOv8 for Brain Tumor Detection in MRI Images. *Journal of Informatics Development*, *4*(2), 54–63. https://doi.org/10.30741/jid.v4i2.1955

INTRODUCTION

Developments in artificial intelligence, especially deep learning, have had a significant impact on various sectors, including the medical field. One rapidly growing application is the use of computer vision for medical image analysis to automatically detect various diseases (Ali et al., 2025). In a medical context, Magnetic Resonance Imaging (MRI) is widely used to detect soft tissue abnormalities, including brain tumors, because it can display the brain’s anatomical structures in detail. Brain tumors are a condition with a high mortality rate and require rapid and accurate diagnosis to improve the success of medical treatment (Iriawan et al., 2024). However, the process of identifying tumors in MRI images is still largely performed manually by medical professionals, which takes a considerable amount of time and may lead to subjectivity in the interpretation of the images (Yang et al., 2024).

Advances in deep learning-based methods offer more efficient solutions through automated detection systems. You Only Look Once (YOLO) is a popular technique for object detection jobs because of its superior real-time detection speed and accuracy (Kang et al., 2025). Several previous studies have shown that the YOLO algorithm is capable of delivering strong performance on medical images, such as in the detection of skin cancer, lung cancer, and brain tumors (Almalki et al., 2022). Research by (Chen et al., 2024) shows that the YOLO-NeuroBoost model is capable of achieving high accuracy in detecting brain tumors in MRI images, while (Almufareh et al., 2024) demonstrates the effectiveness of YOLOv5 and YOLOv7 in brain tumor detection. However, most previous studies have focused on complex architectural modifications or have only conducted tests on public datasets.

Given these circumstances, there remains a research gap regarding the implementation of the YOLOv8 model with a lightweight architecture capable of operating efficiently while maintaining accuracy, as well as testing the model on real clinical data outside the training dataset. Furthermore, the integration of detection models into simple systems that can serve as visualization tools remains limited. Therefore, this study addresses the research questions of how to build a brain tumor detection model using YOLOv8, how the model performs in detecting and localizing tumors based on evaluation metrics, and how well the model can detect new MRI data from real-world clinical settings.

This study aims to design a brain tumor detection model based on the YOLOv8n algorithm for MRI images, use precision, recall, mAP@50, and mAP@50–95 metrics to evaluate the model's performance, and implement the model into a simple web application as a visualization tool for detection results. The application of the lighter and more effective YOLOv8n model for brain tumor detection is the research's scientific contribution, as well as additional testing using real clinical MRI data to evaluate the model’s generalization ability in real-world implementation scenarios.

THEORETICAL FRAMEWORK AND HYPOTHESES

The ideas of deep learning and artificial intelligence serve as the foundation for this study, which enables the system to automatically learn complex patterns from large datasets. Deep learning is widely used in medical image analysis because it can extract hierarchical features without manual feature engineering (LeCun et al., 2015). In this context, computer vision is used to perform object detection tasks, which involve identifying and localizing objects in images using bounding box coordinates. In the medical field, particularly with Magnetic Resonance Imaging (MRI) scans, this technique is crucial because it enables the automatic and efficient detection of abnormal areas, such as brain tumors.

The YOLO (You Only Look Once) technique is a one-stage method for object recognition that uses direct image processing to produce class and position predictions of objects in a single inference step, offering advantages in speed and efficiency. YOLOv8, as the latest version, adopts an anchor-free architecture with improvements to the backbone, neck, and head to enhance multi-scale detection accuracy (Zhang et al., 2024). Figure 1 illustrates the YOLOv8n architecture used in this study.

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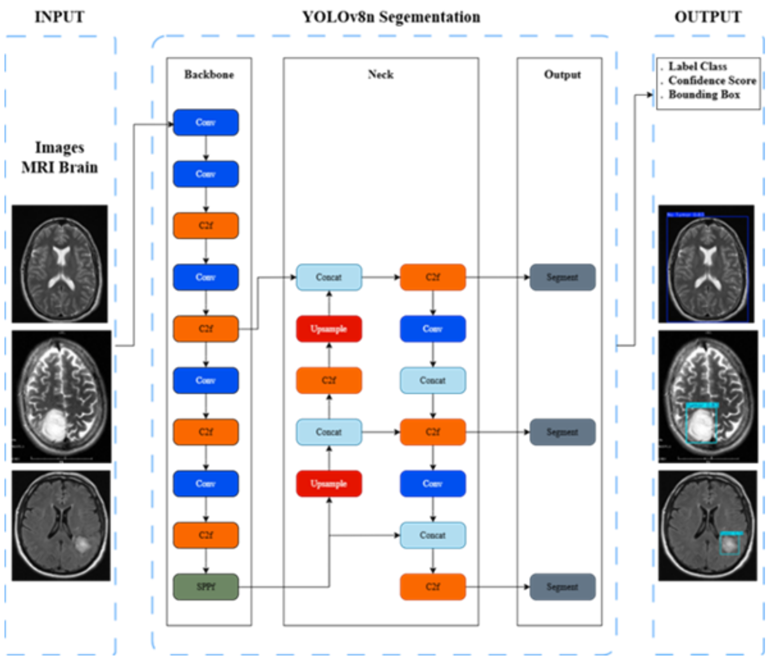

Figure 1. YOLOv8n Architecture
Source: Adapted from [Ultralytics YOLOv8 Documentation]

The following measures are used in this study to evaluate model performance:

1. *Precision*

   $$precision = \frac{TP}{TP+FP}$$

   When assessing a model implementation's performance, precision is essential because it must prevent false positives (Kadyrov & Batyrgaliyev, 2025).
2. Recall

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

   The ratio of true positives to all actual positives is known as recall *(Schlosser et al., n.d.).*
3. Mean Average Precision (mAP)

$$IoU = \frac{Area(Bpred \cap Btrue)}{Area(Bpred \ \cup Btrue)}$$

mAP is used to describe a model's performance in object detection by taking into account precision and recall values. The mAP50 value indicates evaluation at an IoU of 0.50, while mAP50–95 defines the average Average Precision (AP) metric as the average AP value across all IoU thresholds ranging from 0.5 to 0.95 in 0.05 increments (Desmarescaux et al., 2025).

Based on this theoretical framework, this study uses MRI images as input, YOLOv8n as the primary processing model, and the output of the detection, which includes confidence scores, class names, and tumor bounding boxes. The model's detection performance and capacity for generalization on fresh data are then assessed using quantitative criteria.

METHODS

The performance of the You Only Look Once version 8 nano (YOLOv8n) algorithm in identifying and locating brain cancers in Magnetic Resonance Imaging (MRI) scans is assessed quantitatively

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in this work utilizing experimental techniques. Brain MRI pictures of both tumor and non-tumor situations make up the research participants. The dataset comprises 5,015 images, consisting of 5,000 public images obtained from the Kaggle and Roboflow platforms, as well as 15 clinical MRI images from Dr. Haryoto General Hospital and Jordan Hospital (Abu-Srhan et al., 2021), which were used as external validation data. Data selection was based on the images' suitability for the research needs, specifically brain MRI images containing visual information regarding tumor presence and capable of undergoing object annotation.

Data collection was conducted by gathering public datasets and secondary data from hospitals, followed by a manual annotation process using bounding boxes on the Roboflow platform. All images were annotated with bounding boxes based on the target areas corresponding to their respective class labels. The data then underwent preprocessing, including image resizing, grayscaling, and automatic contrast adjustment, as well as data augmentation using horizontal flipping, rotation, and brightness adjustment techniques. After that, the dataset was split into training (70%), validation (20%), and testing (10%) sets. To assess the model's capacity to generalize to new data, the external test data was kept apart from the training process.

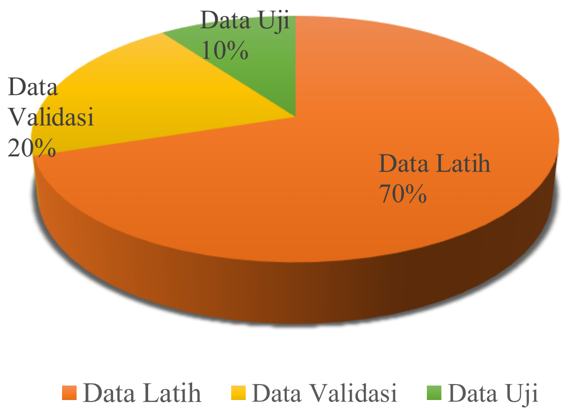

Figure 2. Split Dataset
Source: Author's elaboration

During the experimental phase, the Google Colab platform with NVIDIA Tesla T4 GPU support was used to train the YOLOv8 nano (YOLOv8n) model. A 70% training set, a 20% validation set, and a 10% internal test set were created from the preprocessed dataset. The settings specified in Table 1 were used for the training.

Table 1. Parameter Training Model

No.	Parameter	Nilai
1.	Model	YOLOv8
2.	Epoch	90
3.	Batch Size	16
4.	Image Size	640
5.	Optimizer	SGD
6.	Learning Rate	0.01
7.	Patience	30

Source: Author's configuration based on YOLOv8 documentation (Ultralytics, 2024)

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The best model is saved as a file named best.pt based on the highest validation performance. After the training process is complete, the model is tested using internal and external data to evaluate its ability to generalize to unseen data. The research stages are shown in Figure 3.

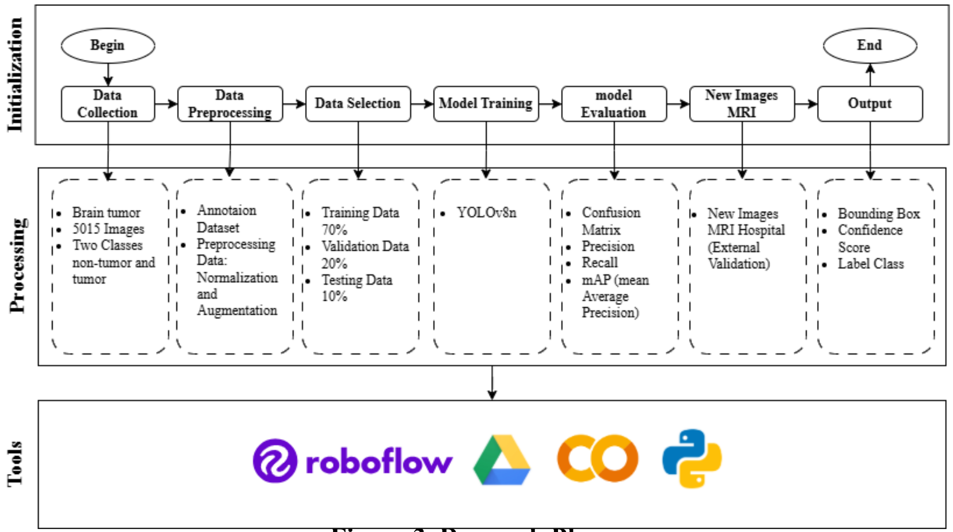


Figure 3. Research Phases
Source: Developed by the authors

RESULTS AND DISCUSSION

a. Performance of the YOLOv8n Model on MRI Images

Table 2. Model Training Results

Class	*Precision*	*Recall*	*mAP@50*	*mAP@50-95*
All	0.969	0.951	0.98	0.723
Tumor	0.947	0.909	0.964	0.636
Non-Tumor	0.992	0.993	0.995	0.81

This study successfully developed a brain tumor detection model based on the YOLOv8n algorithm using a dataset of 5,015 MRI images. The model training results show that the model experienced a gradual decrease in loss values and an improvement in evaluation performance with each epoch, demonstrating that the model was able to learn tumor visual patterns in an appropriate manner without exhibiting noticeable overfitting symptoms. The model achieved a precision of 96.99%, a recall of 94.37%, an mAP@50 of 97.75%, and an mAP@50–95 of 72.01%, as shown in the Table 2. These results show that the model is highly capable of precisely localizing the tumor area and detecting the existence of tumors.

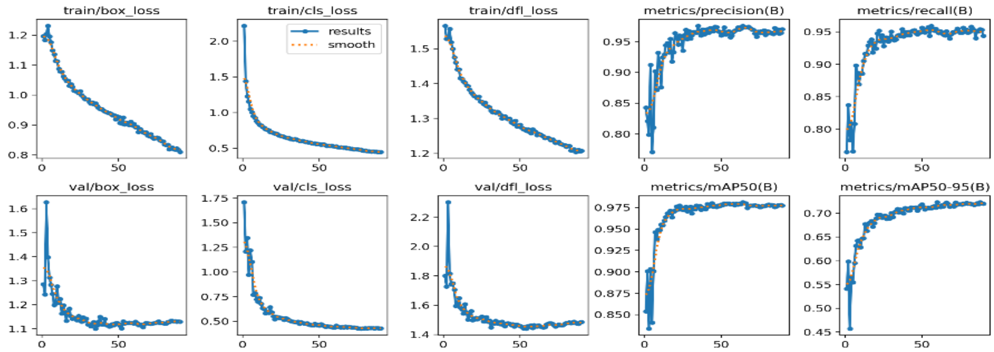


Figure 4. Training Chart
Source: Author's experiment using YOLOv8

Figure 4 that each epoch on the training graph shows a steady decline in box loss, classification loss, and distribution focal loss, indicating that the model has successfully learned the tumor feature patterns optimally.

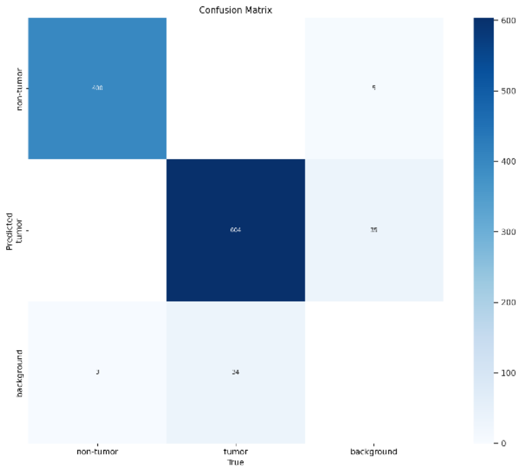


Figure 5. Confusion Matrix
Source: Generated using YOLOv8 validation results

The model still generates a few false positives and false negatives based on the confusion matrix, which are typically brought on by the textural similarity between tumor and normal tissue. This indicates that the use of YOLOv8n as a lightweight model is still capable of delivering competitive performance in the medical imaging domain. These findings align with the concept of the YOLO architecture as a single-stage object detector capable of simultaneously classifying and localizing objects in a single inference process. The implementation of the backbone, neck, and head modules in YOLOv8n allows the model to extract important spatial features from MRI images, including abnormal texture patterns that represent tumors. The use of preprocessing techniques such as grayscale conversion, auto-contrast adjustment, and image augmentation also contributes to improving the quality of the input features, enabling the model to better recognize variations in tumor shape, size, and position. The findings of this work are in line with studies (Chen et al., 2024) that demonstrate the high performance of YOLO-based models in brain tumor diagnosis, as well as research (Almufareh et al., 2024) which demonstrates the effectiveness of the YOLO algorithm in accurately detecting medical objects. However, unlike previous studies that often employed complex architectural modifications, this study shows that the lighter

YOLOv8n model can still deliver optimal results with more efficient computational requirements.

Testing using external data from Dr. Haryoto General Hospital and a hospital in Jordan (Abu-Srhan et al., 2021) was one of the key findings of this study, because it showed how well the model could generalize to real-world, previously unknown data. The model was still able to detect tumor locations in 15 clinical MRI images by displaying bounding boxes, class labels, and confidence scores. To support this explanation, the article can include images of detection results on external MRI data as well as a demonstration of a simple website implementation. However, some performance variations were observed due to differences in image quality, resolution, and clinical data characteristics compared to public datasets. This indicates that the primary challenge in implementing AI-based medical detection systems lies in the diversity of real-world data. Academically, this research contributes to demonstrating that YOLOv8n has the potential to serve as an efficient, accurate, and practical brain tumor detection model to support computer-aided diagnosis systems. The practical implication of this study is the opportunity to develop an automated detection system that can assist medical personnel in performing initial MRI image analysis more quickly, while its scientific contribution lies in testing the model using real clinical data an approach that is still rarely employed in similar studies.

b. Analysis of Tumor Localization Ability

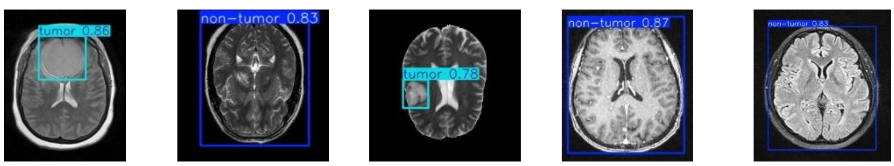
In addition to detecting the presence of tumors, the model also demonstrated strong performance in localizing tumors through bounding box predictions. The model can identify items with a high degree of overlap at an IoU threshold of 0.50, according to a mAP@50 value of 97.75%. In the meantime, a mAP@50–95 result of 72.01% indicates that, despite a reduction, the model's performance is steady at a stricter IoU criterion.

The decrease in the mAP@50–95 value indicates that the model’s primary challenge lies in localization precision when tumor boundaries are irregularly shaped or have low contrast against the surrounding tissue. This condition aligns with the characteristics of brain MRI images, which often feature unclear tumor boundaries, as described by (Yang et al., 2024). Nevertheless, the results of this study still demonstrate competitive performance compared to a previous study by (Almufareh et al., 2024), which reported an mAP value of approximately 94%, and are close to the findings of (Chen et al., 2024), which used a more complex modified architecture.

These findings indicate that lightweight models like YOLOv8n remain capable of delivering high performance without requiring additional complex architectural modifications. From an academic perspective, This indicates that, especially in settings with constrained computational resources, model efficiency might be a vital element in the creation of deep learning-based medical detection systems.

c. Testing on Real-World Clinical MRI Data (External Validation)

The use of fifteen clinical MRI scans from a hospital as external validation data is one of the study's major achievements. The model's capacity to generalize to real-world data is revealed by the fact that these photographs were not utilized in either the training or validation stages.



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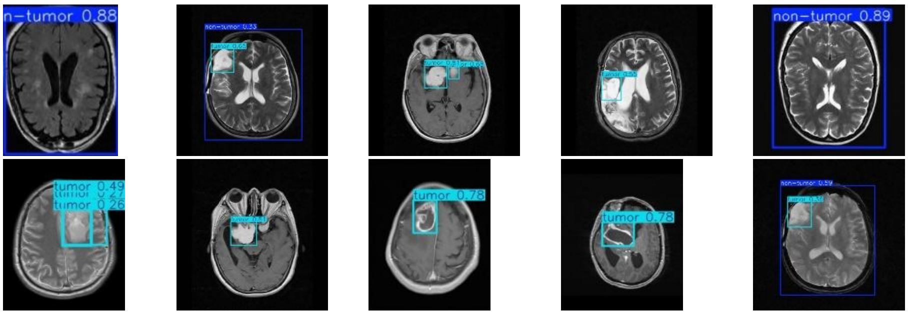

Figure 6. Hasil Test Data Uji External
Figure 6. External Test Data Results

Test results on X-ray images show that the model successfully detected tumors in 13 out of 15 images, with an accuracy rate of 86.7%. Two prediction errors occurred due to low image quality and differences in MRI scanner characteristics compared to the public dataset. Most of the external MRI images display bounding boxes, class labels, and confidence scores ranging from 78% to 90%. These confidence scores indicate that the model has a relatively high level of prediction confidence despite being confronted with real clinical data that varies in image quality, resolution, and MRI device characteristics. These findings suggest that the YOLOv8 model has fairly good generalization capabilities for new data and has the potential to be further developed as a system to support early diagnosis in Magnetic Resonance Imaging.

d. Implementasi Model dalam Aplikasi Web

The best model (best.pt) was then implemented into a simple Flask-based web application to visualize the results of brain tumor detection. The system allows users to upload MRI images and automatically receive detection results, including the tumor location and the model's confidence score.

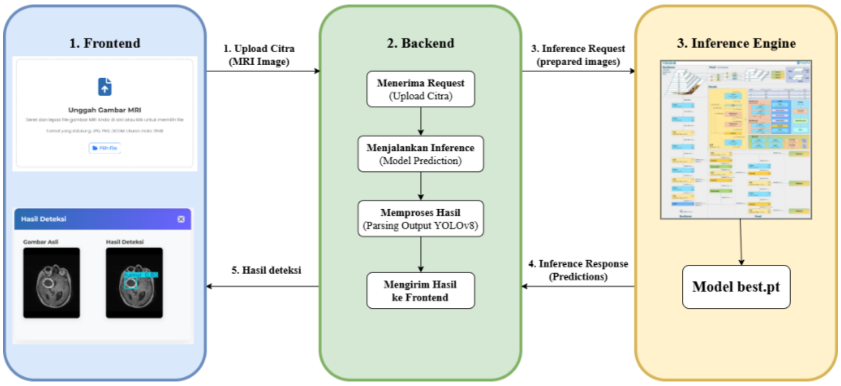

Figure 7. Alur Kerja Website
Source: Developed by the authors

This implementation demonstrates that the model goes beyond the stage of academic experimentation and has the potential to be translated into real-world systems that can be used for computer-aided diagnosis. Although the application developed is still relatively simple, as shown in Figure 7, this research makes a practical contribution by bridging the gap between the development of artificial intelligence models and their more practical implementation in the healthcare field.

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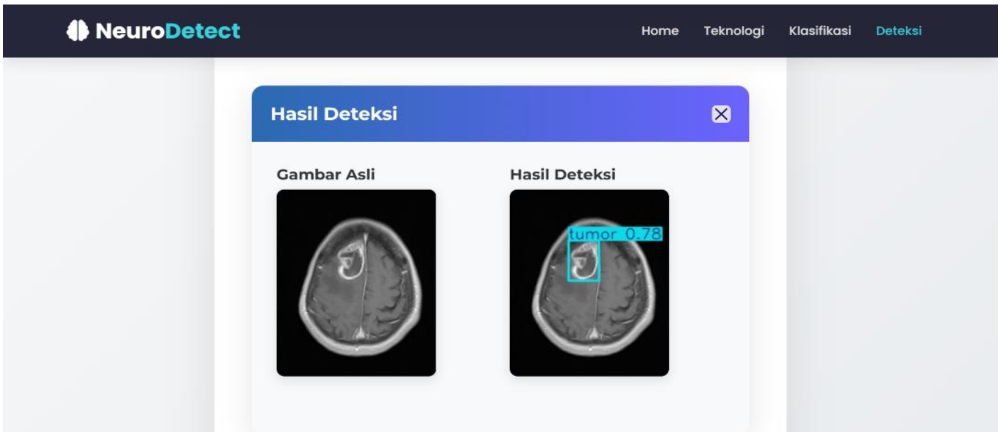

Figure 8. Antar Muka Hasil Website
Source: Developed by the authors

CONCLUSION

This study successfully developed a brain tumor detection model based on the YOLOv8n algorithm for MRI images, aimed at automatically identifying and localizing tumor areas. With a precision of 96.99%, a recall of 94.37%, an mAP@50 of 97.75%, and mAP@50–95 of 72.01%, the findings demonstrate the model's strong performance based on quantitative evaluation. Additionally, the model was also capable of detecting tumors in previously unseen clinical MRI data, demonstrating its generalization ability to unseen data. These results satisfy the study goal of developing a high-performance deep learning-based detection model and solve the research issue statement that YOLOv8n may be employed for the detection and localization of brain cancers in MRI images.

This study shows that the lightweight YOLOv8n architecture can still achieve excellent accuracy and theoretically supports the use of the YOLO algorithm in medical imaging, namely, in brain tumor diagnosis. Practically, the findings of this study could be the basis for the creation of AI-based diagnostic support systems that are quicker and more effective. However, this study has limitations regarding the still-limited amount of external clinical data and the lack of detailed tumor segmentation. In order to increase the accuracy of tumor area analysis, it is advised that future studies employ a bigger clinical dataset, test alternative YOLO architecture variations, and create segmentation techniques.

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