International Journal on Perceptive and Cognitive Computing (IJPCC) Vol 12, Issue 1 (2026)
https://doi.org/10.31436/ijpcc.v12i1.639

Comparative Evaluation of Lightweight CNN and YOLOv8 Models for Brain Tumor Detection in Resource-Constrained Settings

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(Received: 27th November 2025; Accepted: 12th January 2026; Published on-line: 30th January, 2026)

Abstract—Brain tumor detection is essential for timely diagnosis, early intervention, and effective treatment planning. With advancements in artificial intelligence (AI), deep learning methods have emerged as powerful tools in medical imaging, offering automated, consistent, and efficient detection of brain abnormalities. However, achieving clinically reliable performance requires models that can accurately differentiate between tumor and non-tumor cases. This paper investigates and compares the performance of two deep learning models which are a lightweight Convolutional Neural Network (CNN) and the You Only Look Once (YOLO) YOLOv8 model for brain tumor classification in resource-constrained setting. Both models were trained and evaluated using the BR35H dataset, which comprises 3,000 MRI scans categorized into tumor and non-tumor classes. The performance of the models are evaluated using accuracy, precision, recall, F1-score as well as inference time supplemented by confusion matrix, ROC analysis and Grad-CAM visualizations to assess class-wise prediction performance. The experimental results indicate that YOLOv8 demonstrated high predictions across both tumor and non-tumor categories. YOLOv8 outperformed the CNN, achieving an accuracy of 0.998, precision of 0.997, recall of 1.00, and an F1-score of 0.998. However, only a minimal difference was observed in the inference time per image between YOLOv8 and the CNN, with YOLOv8 being slower by just 10.6 ms. Finally, the results demonstrate YOLOv8's robustness and reliability for early tumor detection, a critical factor in preventing diagnostic delays. The findings further highlight YOLOv8's suitability for integration into clinical decision-support systems, particularly in resource-constrained environments where accurate and fast automated diagnosis can significantly enhance patient care.

Keywords— deep learning, CNN, YOLO, Brain tumor, detection

I. Introduction

Brain tumors remain a critical global health concern, and early diagnosis is essential for improving treatment outcomes and patient survival. Magnetic Resonance Imaging (MRI) is the most widely used modality for detecting brain abnormalities due to its high contrast resolution and non-invasive nature. MRI is the standard non-invasive imaging modality for identifying brain tumors due to its superior soft tissue contrast and high-resolution capabilities, which allow clinicians to visualize tumor morphology, size and location. However, in many clinical settings, particularly in developing countries, the number of trained radiologists or experts is insufficient to meet the increasing demand for diagnostic imaging[1][2]. This shortage contributes to a heavy workload and prolongs the detection process, as manual interpretation of MRI scans is inherently time-consuming, potentially causing delays in intervention and treatment planning. Brain tumors are among the most life-threatening neurological disorders worldwide, often requiring prompt and accurate diagnosis to guide effective treatment and improve patient outcomes[3][4][5]. Consequently, brain tumor detection and classification using MRI scans are critical tasks in medical diagnostics, significantly influencing patient outcomes through timely and precise diagnosis.

Advancements in deep learning, particularly Convolutional Neural Networks (CNNs) and You Only Look Once (YOLO) frameworks, have revolutionized the field of medical image analysis, offering promising solutions for the automated detection and classification of brain tumors[6][7][8][9][10]. CNNs are the deep learning models designed to process and analyze visual data. The model excels in tasks such as object detection, image segmentation, and classification by automatically learning hierarchical features from the input images. CNNs have been widely used in brain tumor detection due to their ability to accurately identify and segment tumor regions in MRI

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scans[7][11]. On the other hand, YOLO is an object detection framework designed to perform both localization and classification within a single unified architecture, enabling the model not only to identify the presence of a tumor but also to precisely localize its region within an MRI slice. Its deeper and optimized architecture enhances feature representation, improving sensitivity to subtle tumor boundaries and small-scale abnormalities.

Given the urgent need for accurate and timely tumor detection to improve treatment outcomes and survival rates, this research investigates the detection performance of these two CNN and YOLO models for brain tumor classification. Experiments were conducted using the BR35H brain tumor MRI dataset to evaluate both a lightweight CNN and the YOLOv8 model. YOLOv8 was selected for its advanced feature extraction and robust detection capabilities, while the lightweight CNN serves as a baseline due to its simplicity and controlled architectural design. By comparing these two models, the research provides a focused analysis of performance, robustness and clinical applicability, particularly in resource-constrained clinical environments. Limiting the evaluation to these two models allows for a focused and practical investigation. By analyzing their strengths and limitations under identical experimental conditions, this research provides meaningful insights into selecting suitable AI architectures for clinical deployment. The findings contribute to the development of efficient, accurate, and explainable computer-aided diagnosis (CAD) systems for brain tumor detection. The contributions of this paper are as follows:

- Conducts a focused evaluation in which a lightweight CNN serves as a conventional, low-complexity feature-extraction classifier, while YOLOv8 represents a detection-oriented, multi-scale architecture.
- Provides a comparative evaluation of CNN and YOLOv8 for binary brain tumor detection using MRI scans, highlighting their practical applicability in clinical and resource-constrained settings, as well as their suitability for deployment in diverse healthcare environments.
- Analyzes detection performance of both models across tumor and non-tumor classes to quantify diagnostic accuracy, while employing explainable AI techniques to evaluate model interpretability.

The remainder of this paper is structured as follows: Section II presents related work on brain tumor detection. Section III discusses the methodology employed in this research. The experimental setup is described in Section IV, followed by results and discussion in Section V. Finally, conclusions and future work are presented in Section VI.

II. Related work

Deep learning approaches have been widely applied to brain tumor detection and classification using MRI images. The application of deep learning techniques for brain tumor classification has evolved significantly over the past few years. Early research for brain tumor classification focused primarily on CNN-based architectures. CNN-based methods have been widely used for brain tumor classification due to their strong feature extraction capabilities. Sajjad et. al proposed a multi-grade brain tumor classification framework using CNNs combined with image enhancement techniques, reporting strong performance across glioma and meningioma detection tasks[12]. Similarly, Deepak et. al employed transfer learning on pre-trained CNN, demonstrating that CNN architectures can effectively capture hierarchical tumor features from MRI scans[13]. O the other hand, Daniel Reyes et al. compared various CNN architectures including VGG, ResNet, EfficientNet, and ConvNeXt for brain tumor classification [14]. In their work, the CNN model able to achieve promising results with the best model reaching 98.7% accuracy on datasets containing over 3000 images of gliomas, meningiomas, and pituitary tumors. The research demonstrated that ResNet, MobileNet, and EfficientNet were the most accurate networks, with MobileNet and EfficientNet showing superior performance in terms of computational complexity. CNNs have been the backbone of many automated brain tumor diagnosis systems due to their ability to extract hierarchical spatial features and achieve high accuracy on medical images. CNNs have been widely used for brain tumor detection due to their robust feature extraction capabilities. The standard CNN classification models also able to provide a probabilistic output without directly indicating the tumor's spatial location. Various studies have demonstrated the effectiveness of CNNs in classifying and detecting brain tumors from MRI scans and have shown promising results in terms of accuracy, precision, and recall metrics particularly for limited labeled MRI data[15]. While CNNs are computationally efficient and suitable for resource-constrained environments, their relatively shallow feature extraction pipelines can limit performance on complex or heterogeneous tumor appearances.

CNNs have been extensively used for brain tumor detection due to their ability to automatically extract hierarchical features from medical images. Various CNN architectures, such as EfficientNet, ResNet, and VGG-16, have demonstrated high accuracy in tumor detection tasks[16][17][18]. EfficientNet able to achieved a promising accuracy by optimizing depth, width, and resolution

simultaneously, making it both accurate and computationally efficient[19]. However, CNNs often struggle with capturing long-range dependencies and contextual information, which are crucial for accurate tumor classification[20]. Transformers, particularly Vision Transformers (ViTs), have been introduced to address the limitations of CNNs. ViTs use the self-attention mechanisms to capture both local and global features, significantly improving the model's ability to understand complex spatial relationships in medical images[21]. ViTs model able to achieve high accuracy in classification task. Jia et al. proposed a transformer-augmented deep learning model for tumor detection under cystoscopy, demonstrating improved feature representation and classification accuracy[22]. Despite their effectiveness, ViTs can be computationally intensive and require large datasets for training[23].

Hybrid models have also been developed typically using CNNs for initial feature extraction and Transformers for capturing long-range dependencies. Jaffar et. al proposed a hybrid model combining ResNet50 and a Transformer encoder demonstrated superior performance in classifying brain tumors, achieving an accuracy of 99.2%[20]. While Sankari et. al. integrated CNNs with ViTs and achieved a precision of 98.7%, outperforming both standalone CNN and Transformer models[24]. Hybrid models have consistently shown higher accuracy compared to standalone CNN or Transformer models. For instance, a CNN-ViT hybrid achieved an accuracy of 98%, surpassing the standalone models[25]. By combining local feature extraction of CNNs with the global context modeling of Transformers, hybrid models provide a more comprehensive feature representation[26]. These models have demonstrated better generalization to unseen data, making them more reliable for clinical applications[26]. While these approaches achieve strong performance, Hybrid models can be computationally demanding, requiring significant processing power and memory[23][24]. In addition, large and diverse datasets are often required to train these models effectively, which can be a limitation in medical imaging where data is scarce[23]. Despite their accuracy, integrating these models into existing clinical workflows poses challenges especially related to computational complexity and data requirements, which may limit practical deployment in clinical settings particularly in resource-constrained environments.

In contrast, the YOLO models balance accuracy and efficiency where the models reduce computational complexity while maintaining high detection accuracy[27]. YOLO models represents a class of single-stage object detectors designed to prioritize speed while maintaining competitive accuracy. This architecture simultaneously predicts bounding boxes and class probabilities, making it well suited for real-time analysis where detection latency is an important performance factor[28]. The detection architectures of a YOLO model have been progressively developed. Their model architectures have marked a significant advancement in many classifications task including brain tumor detection and classification. In YOLOv1 model, a unified detection framework is introduced in the model where it enabled real-time object detection[28]. On the other hand, the YOLOv2 and YOLOv3 model improved feature extraction, multi-scale detection, and training stability[29]. YOLOv4 model further enhanced accuracy using advanced backbone networks and data augmentation strategies[30]. While YOLOv5 and YOLOv6 models continued the trend with improved lightweight architectures for deployment efficiency. YOLOv5 model was adopted by Fayez Ghufran et al. for brain tumor identification and classification task. They compared the performance of YOLOv5 model with Faster R-CNN[31].In their work, they proposed 9-layer CNN and able to achieved an accuracy of 98.21%, highlighting the potential of YOLO-based model to support real-time tumor detection with lower computational requirements compared to earlier models. The YOLO models continued to evolve, with each version introducing architectural improvements to enhance detection performance. The YOLOv7 model incorporated extended efficient layers and model re-parameterization strategies to maximize detection performance[32]. While in YOLOv8, significant architectural improvements over previous YOLO variants being introduced, including decoupled heads for classification and localization, a more efficient CSPDarknet-based backbone, and enhanced training optimization strategies[33]. In YOLOv8 model, it also includes a dedicated classification mode (YOLOv8-cls), enabling the framework to operate not only as a detector but also as a high-performance image classifier. This dual capability makes the YOLOv8 model particularly well-suited for medical image analysis tasks that demand both accuracy and efficiency. Its optimized inference pipeline, reduced computational complexity, and superior generalization performance make it an appealing choice for brain tumor classification compared with earlier YOLO versions. Aniket Prabhu Taradale et al. specifically focused on YOLOv8 for brain tumor segmentation and classification, achieving promising performance metrics including 95% F1-Score, 96.20% precision, 93.6% recall, and 97.2% mAP50[34]. Their work emphasized YOLO's real-time detection capabilities, representing a significant improvement over segmentation method. On the other hand, Zougari et al. reported a detection accuracy of 0.85 using YOLOv8 on a dataset of 1101 MRI images[35]. Similarly Verma et al. also reported that YOLOv8 demonstrated superior performance in brain tumor

https://doi.org/10.31436/ijpcc.v12i1.639

classification, successfully distinguishing glioma, meningioma, and pituitary tumors with an accuracy of 99.12%[36]. YOLOv8 model fine-tuned for brain tumor detection, achieves competitive accuracy and efficiency. Its balanced performance between precision and computational efficiency makes it well-suited for deployment in clinical environments, where both reliability and processing speed are critical[37].

Despite YOLOv8 provides advanced performance, CNN models remain essential as it offers a simpler architectural design, allow direct control over feature extraction layers, and are widely adopted in medical imaging. These characteristics make CNNs an ideal baseline model for comparative evaluation, allowing a clear assessment of performance improvements offered by more advanced architectures such as YOLOv8. Both CNN and YOLO-based models have shown strong potential in brain tumor detection from MRI images. CNN particularly effective at hierarchical feature extraction and often achieve high classification accuracy, although they tend to be computationally intensive. In contrast, YOLOv8 offers real-time detection capabilities and highly efficient computation, attributes that are critical for clinical environments requiring rapid decision support. YOLOv8 able to maintains competitive and often superior accuracy across various classification task[9][36].

Although CNN and YOLO-based models have shown strong performance in brain tumor detection and classification, there are limited studies that directly compare these two approaches under a unified experimental setup. This research conducts a direct comparison of a lightweight CNN and YOLOv8 using the BR35H dataset for binary tumor classification, explicitly considering resource-constrained environments and using identical training hyperparameters and evaluation protocols. Performance is assessed not only through accuracy, precision, recall, F1-score including inference time but also with confusion matrix analysis, ROC curves, and Grad-CAM visualizations, providing both quantitative and interpretable insights. These enables a clear understanding of the models' relative performance, suitability for deployment in low-resource settings, and reliability for clinical decision support, particularly in minimizing false negatives that could delay diagnosis and treatment. By explicitly controlling dataset, task type, model version, and evaluation setup, this reseaerch provides an insight for future research in clinically relevant, resource-constrained brain tumor detection and classification.

III. METHODOLOGY

This research implements an experimental workflow for brain tumor detection using two deep learning models which are CNN and YOLOv8 classification model. The workflow is illustrated in Fig. 1. which outlines the sequential stages of dataset preparation, model development, hyperparameter optimization and performance evaluation. Each of these steps will be discussed in the following subsections.

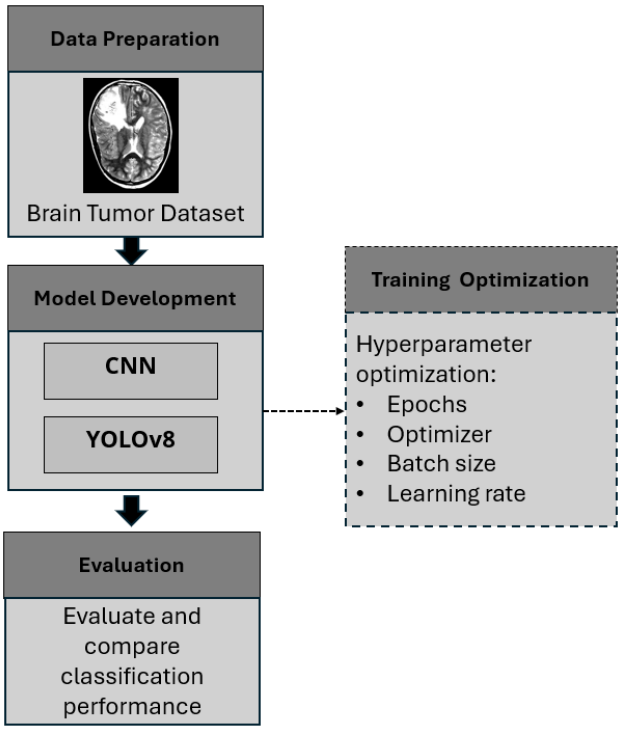

Fig. 1. Workflow of brain tumor detection using two deep learning models: CNN and YOLOv8.

A. *Data Preparation*

In this research, the BR35H dataset[38], *comprising 3,000 MRI brain images evenly divided into tumor and no-tumor classes, was employed due to its suitability for binary brain tumor detection. Its balanced class distribution minimizes bias from class imbalance, ensuring fair and reliable training and evaluation of both CNN-based classifiers and detection-oriented models such as YOLOv8. In addition, BR35H's standardized structure and adoption in prior research enable clinically meaningful and unbiased performance comparisons across different deep learning architectures.*

B. *Model Development*

To identify the most suitable model for brain tumor classification, two deep learning models namely, CNN and YOLOv8 were developed. Each model is described in detail in the following subsections.

I) Convolutional Neural Network (CNN): The CNN model architecture employs a convolutional neural

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network as both the feature extractor and classifier, as illustrated Fig. 2. The CNN processes each MRI scan through a sequence of structured layers, including the input layer, convolutional layers, pooling layers, and fully connected layers. Each layer performs a specific computational transformation that converts the MRI image into a high-dimensional feature representation suitable for tumor classification. Three convolutional layers are used in the CNN architecture, each with progressively increasing depth to capture more complex spatial patterns at successive levels of abstraction. The first convolutional layer is responsible for detecting low-level features such as edges, contours, and basic intensity gradients within the MRI scan. The second convolutional layer extracts mid-level visual patterns, including textural differences and structural variations commonly associated with tumor regions. The third convolutional layer captures high-level, more abstract features, such as the overall shape, size, and spatial relationships of tumor regions, which are critical for accurate classification and localization. Each convolutional layer utilizes a set of learnable kernels that slide across the MRI image to detect localized spatial features. These filters generate feature maps by computing weighted dot products, enabling the network to encode spatial irregularities, lesion boundaries, and tumor shapes. Following each convolutional layer, a corresponding max-pooling layer is applied to reduce spatial resolution, retain dominant features, and decrease computational complexity. The pooling layers also help introduce translation invariance, enabling the network to detect tumor features regardless of their precise position within the MRI. After feature extraction, the flattened output is passed into fully connected layers that learn global feature interactions. The final classification is performed, which outputs the probability distribution across the two classes which are tumor and no tumor.

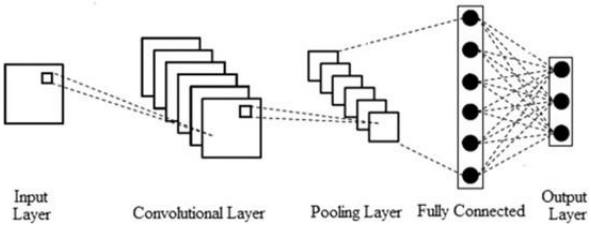

Fig. 2. CNN model Architecture[39]

2) *YOLOv8*: The YOLOv8 architecture consists of three main components which are the backbone, neck, and detection head. Each playing a critical role in feature extraction, multi-scale feature aggregation, and final tumor prediction. The backbone extracts hierarchical features from MRI images through a series of convolutional and C2f blocks. The stem layer uses a 3×3 convolutional kernel to reduce computational cost, while the C2f blocks efficiently process features at multiple pyramid levels (P1–P5). Low-level features (P1) capture fine details, while higher-level features (P5) encode semantic information, allowing detection of tumors of varying sizes and shapes. The neck aggregates multi-scale features from the backbone to improve detection accuracy. Using a feature pyramid approach, it concatenates features across pyramid levels (P1–P5) without requiring identical channel dimensions, reducing parameter count and tensor size while maintaining robust multi-scale tumor detection. The SPPF module is also applied to capture contextual information across varying receptive fields. The detection head receives the fused features from the neck and predicts tumor centers, bounding box dimensions, and class probabilities in an end-to-end manner. This eliminates the need for anchor boxes, which are commonly required in CNN-based models. The architectural structure of YOLOv8 is illustrated in Fig. 3

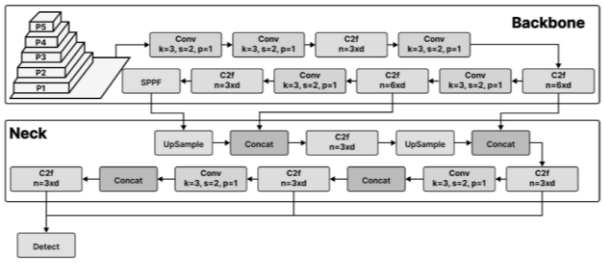

Fig. 3. YOLOv8 architecture structure[40]

Unlike CNNs, which are effective for feature extraction and classification but may struggle with tumors of irregular shapes or varying sizes, YOLOv8 performs end-to-end detection, simultaneously localizing and classifying tumors. This capability leads to improved detection accuracy. YOLOv8 directly predicts object centers using a center-based detection strategy, enabling precise localization of irregularly shaped tumors and enhancing generalization across diverse tumor morphologies. These features make YOLOv8

https://doi.org/10.31436/ijpcc.v12i1.639

particularly suitable for brain tumor detection tasks where both accurate classification and precise localization are critical. In addition, YOLOv8 incorporates the Spatial Pyramid Pooling Fast (SPPF) module to capture features at multiple scales, which is important for detecting tumors of varying sizes while maintaining computational efficiency.

IV. EXPERIMENTAL SETUP

To evaluate the performance of both models for brain tumor classification, a series of experiments were conducted using the BR35H MRI dataset and implemented in Python. Both models were trained under identical training hyperparameters to ensure a fair comparison, as summarize in Table I. Adam optimizer with a learning rate of 0.001, a batch size of 16, and 30 epochs are used in the experiments. Prior to training, all MRI images from the BR35H dataset were preprocesses, including resizing to 224×224 pixels. The 224×224 pixels image size was chosen to balance computational efficiency and the preservation of critical anatomical details, as larger images significantly increase training time and memory requirements, while smaller images may lose important tumor features that are essential for accurate detection. The batch size of 16 was selected to optimize memory usage while maintaining stable gradient updates during training. The models were trained for 30 epochs, providing sufficient iterations for convergence and adequate learning while minimizing the risk of overfitting. The selection of image size, number of epochs, and batch size in these experiments follows the settings reported in previous studies[41][42][43][44][45][46][47][48][49]. All the experiments were performed in a CPU-based environment, demonstrating the feasibility of the approach in resource-constrained settings.

Table I.

Hyperparameter settings for CNN and YOLOv8 models training

Model / Hyperparameter	CNN	YOLOv8
Optimizer	Adam	Adam
Activation Function	ReLU (Rectified Linear Unit)	SiLU (Sigmoid Linear Unit / Swish)
Kernel size	3×3	3×3
Number of Conv Layers	3	225
Loss Function	CrossEntropyLoss	CrossEntropyLoss
Image Size (pixels)	224×224	224×224
Learning rate	0.001	0.001
Epoch Size	30	30
Batch Size	16	16

The BR35H brain tumor dataset, consisting of two classes which is tumor and non-tumor is used for evaluation, with details in Table II and sample images shown in in Fig. 4.

Table II

BR35H Dataset Distribution

Classes	Number of Images
Tumor	1500
Non-Tumor	1500
Total	3000

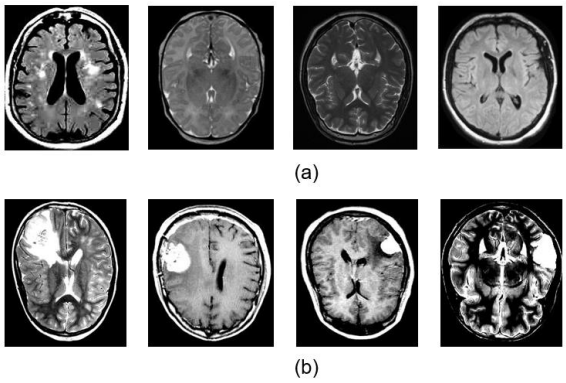

Fig. 4. Example images in BR35H dataset (a) non-tumor (b) tumor

For model evaluation, an 80:20 train-test split was applied to the dataset for training and testing. This ratio is adopted in this research following prior studies, as most deep learning-based works in the literature use similar splits for training and evaluation [50][51][52][53][54][55]. Following these ratios, the training set comprises 2,400 images, while the remaining 600 images are used for testing, as detailed in Table III.

Table III

Dataset Distribution for Training and Testing

Dataset Split	Training Set (80%)	Testing Set (20%)
Non-Tumor	1200	300
Tumor	1200	300
Total	2400	600

V. RESULTS AND DISCUSSION

In this research, the performance of the brain tumor classification models was evaluated using four performance metrics which are accuracy, precision, recall and F1-score including inference time. Accuracy represents the overall

https://doi.org/10.31436/ijpcc.v12i1.639

proportion of correct predictions across both tumor and non-tumor cases. Precision reflects the proportion of correctly identified tumor cases among all instances predicted as tumor, while recall measures the model's ability to detect all positive cases. The F1-score provides a mean of precision and recall, offering a balanced performance indicator. The inference time per image was recorded in each experiment to evaluate computational efficiency. The formulas for calculating each of the evaluation metrics are defined as follows:

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

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

$$F1\ Score = 2x \frac{(Precision\ x\ Recall)}{Precision + Recall} \quad (4)$$

where TP, FP, TN and FN are defined in Table IV.

Table IV.
Terminology and derivations

Terminology	Derivations
TP (True Positive)	Tumor image correctly identified as tumor
TN (True Negatives)	Non-tumor image correctly identified as non-tumor
FP (False positives)	Non-tumor image incorrectly identified as tumor
FN (False negatives)	Tumor image incorrectly identified as non-tumor

A comparison of the performance of CNN and YOLOv8 in classifying brain tumor MRI images using the BR35H dataset are presented in Table V.

Table V

Comparative results (accuracy, precision, recall and inference time per image) for CNN and yolov8

Models	Accuracy	Precision	Recall	F1-score	Inference Time per Image (ms)
CNN	0.980	0.983	0.977	0.980	4.5
YOLOv8	0.998	0.997	1.00	0.998	15.1

Overall, the results demonstrate that both models achieved high accuracy, precision, recall, and F1-score, confirming their effectiveness for binary brain tumor detection. However, slightly lower performance was observed with the CNN model, which achieved an accuracy of 0.980, a precision of 0.983, a recall of 0.977, and an F1-score of 0.980. While CNN performed well, YOLOv8 demonstrated superior performance across all metrics, achieving an accuracy of 0.998, a precision of 0.997, recall of 1.00, and an F1-score of 0.998. Although the CNN results were slightly lower than YOLOv8, the promising results shown in the CNN methods indicate that the CNN architecture is capable of learning discriminative features from MRI images and provides reliable classification performance. The slight discrepancy between precision and recall shows that CNN occasionally misclassified a small number of tumor or non-tumor samples, which is expected given its relatively shallow architecture compared to modern deep learning models. In contrast, the value of 1.00 in recall implies that YOLOv8 successfully identified all tumor samples in the test set without missing any cases. This is very important aspect especially in medical diagnosis where false negatives carry significant clinical risks. The enhanced performance is due to YOLOv8's advanced architecture, which incorporates optimized convolutional blocks, improved feature extraction modules, and more efficient gradient flow, enabling the model to capture complex patterns in MRI images more effectively than the CNN. While both models performed strongly, the difference in accuracy and recall highlights YOLOv8's model is more robustness, generalizable and sensitive in detection. These results shows that YOLOv8 is more suitable for deployment in real-time clinical decision-support systems, where high reliability and low error rates are essential. Overall, YOLOv8 outperformed the CNN in accuracy, precision, recall and F1-Score, demonstrating its effectiveness as a modern deep learning model for brain tumor classification. Although YOLOv8 has a slightly higher inference time of 15.1 ms per image, which is only 10.6 ms longer than the CNN, it achieves superior performance and enhanced interpretability. The trade-off between speed and accuracy shows that YOLOv8 is well-suited for real-time clinical decision-support systems, and its inference time remains feasible for deployment in resource-constrained environments, making it a viable option for clinical application.

The confusion matrix analysis also further confirms that misclassification rates were extremely low for both classes especially for YOLOv8 as shown in Fig.5. Fig.5 (a) presented CNN results while Fig.5 (b) presented YOLOv8. CNN results in Fig.5 (a) show that the model correctly classified 295 non-tumor images and 293 tumor images. The CNN model generated 5 false positives, where non-tumor cases were incorrectly predicted as tumor, and 7 false negatives, where tumor cases were incorrectly classified as non-tumor. These misclassifications indicate that although the CNN achieves high accuracy, its sensitivity to subtle tumor features remains slightly

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limited, particularly in cases where tumor margins appear blurred or low contrast. In contrast, the confusion matrix of YOLOv8 as shown in Fig.5 (b) demonstrates substantially stronger performance. The model correctly predicted all 300 non-tumor cases and 299 tumor cases, resulting in zero false positives and only one false negative. This reflects YOLOv8's superior capacity to distinguish between tumor and non-tumor patterns, benefiting from deeper feature extraction, multi-scale representation learning, and an optimized detection head. The near-perfect separation between the two classes further explains its significantly higher precision, recall and F1-score compared to the CNN model.

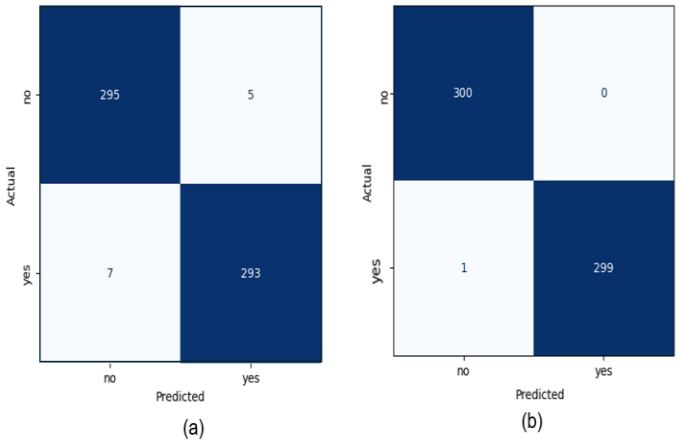

Fig. 5. Comparison confusion matric (a) CNN and (b) yolov8 model

Overall, the results clearly demonstrate that YOLOv8 outperforms the CNN in both recall and precision. This superior performance indicates that YOLOv8 is more suitable for deployment in real-time or clinical decision-support settings, particularly where minimizing false negatives is crucial. Detecting tumor cases accurately is essential, as missed detections can delay diagnosis and treatment, potentially worsening patient outcomes. YOLOv8's ability to significantly reduce false negatives, therefore makes it highly reliable for early and clinically sensitive tumor detection.

To further evaluate the comparative performance of the CNN and YOLOv8 models, The Receiver Operating Characteristic (ROC) curves for the CNN and YOLOv8 models are presented in Fig. 6(a) and Fig. 6(b), respectively.

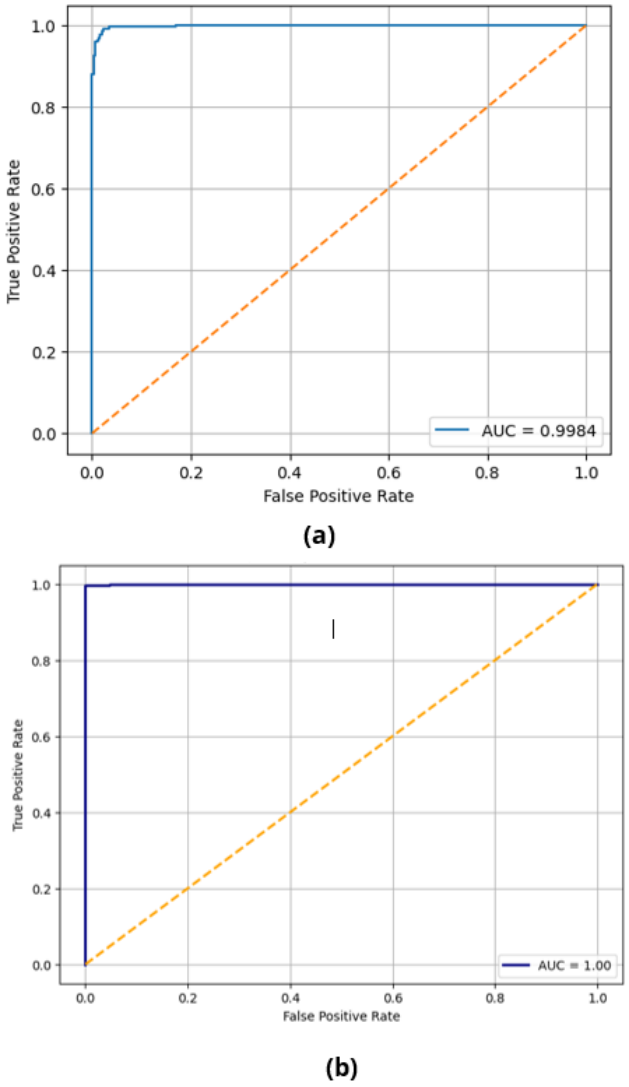

Fig. 6. Comparison ROC Curve (a) CNN and (b) yolov8 model

These ROC curves provide a threshold-independent evaluation of the classification performance of both models on the dataset tested. The curve illustrates the trade-off between the True Positive Rate (TPR) and False Positive Rate (FPR) across varying decision thresholds, providing a threshold-independent assessment of classification performance. As shown in Fig. 6 (a), the CNN model achieves an Area Under the Curve (AUC) of 0.9984, indicating excellent discriminative capability between tumor and non-tumor classes. The curve rises steeply toward the upper-left corner, reflecting a high true positive rate with a relatively low false positive rate across most thresholds. This shows that the CNN model is effective in correctly identifying tumor cases (high TP) while maintaining a low rate of misclassifying non-tumor images as tumor (low FP). While the ROC curve for the

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YOLOv8 model as presented in Fig. 6 (b) demonstrates an AUC of 1.00, indicating near-perfect separation between tumor and non-tumor classes on the dataset tested. The curve closely follows the left and top borders of the ROC space, shows that YOLOv8 consistently achieves a very high true positive rate with minimal false positives. This near-perfect performance is due to the characteristics of the BR35H dataset, which is relatively clean, balanced, and well-curated, with clearly defined tumor and non-tumor cases. This demonstrates strong robustness across decision thresholds, reducing the likelihood of false negatives (FN), which is particularly critical in clinical settings where missed tumor detections can delay diagnosis and treatment.

Overall, the ROC analysis highlights that both models exhibit strong classification capability; however, YOLOv8 demonstrates superior threshold stability and robustness. Rather than relying solely on point estimates such as accuracy, the ROC results confirm that YOLOv8 maintains reliable performance across a wide range of operating points, supporting its suitability for automated brain tumor detection, especially in clinical and resource-constrained environments where consistent decision-support systems is essential.

While the ROC curve analysis confirms the strong discriminative capability of both models across varying decision thresholds, such performance metrics alone are insufficient to establish clinical trustworthiness. In medical imaging applications, it is equally important to understand how and why a model arrives at its predictions, particularly in brain tumor detection where erroneous or poorly justified decisions may have serious clinical consequences. Therefore, we further investigate the internal decision-making behavior of the CNN and YOLOv8 models using Gradient-weighted Class Activation Mapping (Grad-CAM). This explainable artificial intelligence (XAI) approach enables visualization of the spatial regions within MRI scans that most strongly influence model predictions, thereby facilitating assessment of whether the models attend to clinically meaningful tumor regions or rely on indirect contextual cues or imaging artifacts. Such interpretability analysis is essential not only for validating model reliability under real clinical variability but also for supporting safe human-in-the-loop deployment, where automated predictions are intended to assist rather than replace expert radiological judgment. Fig. 7 (a) and Fig. 7 (b) illustrates representative Grad-CAM visualizations for the CNN and YOLOv8 models, providing insight into how each architecture using spatial information within brain MRI scans to support its predictions. In these visualizations, warmer colors indicate regions that contribute most strongly to the model's decision, allowing direct assessment of whether the learned attention aligns with the visible tumor anatomy.

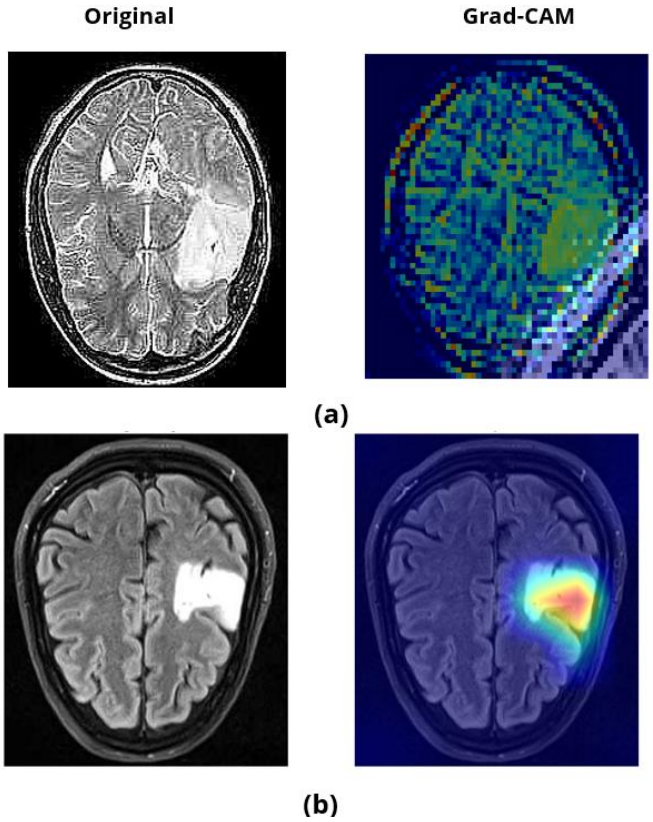

Fig. 7. Grad-CAM visualizations for brain tumor detection (a) CNN and (b) YOLOv8

As shown in Fig. 7 (a) the CNN model exhibits a relatively diffuse and fragmented activation pattern. Although the original MRI clearly demonstrates a prominent hyperintense lesion consistent with a brain tumor, the corresponding Grad-CAM heatmap highlights multiple regions of moderate importance distributed across both tumorous and non-tumorous areas. The absence of a sharply localized focus suggests that the CNN may be relying on a combination of global image characteristics, contextual anatomical cues, or correlated features rather than selectively attending to the pathological region itself. While this behaviour does not preclude high classification performance, it raises concerns regarding interpretability and robustness, particularly in real clinical environments where MRI data are inherently heterogeneous. Variations in scanner vendors, magnetic field strengths, acquisition protocols (e.g., T1-, T2-, or FLAIR-weighted imaging) and the presence of noise or motion artifacts may alter these contextual cues, potentially limiting generalizability

when models depend on indirect or dataset-specific patterns.

In contrast, Fig. 7 (b) demonstrates that the YOLOv8 model produces a markedly more focused and clinically intuitive activation map. The Grad-CAM heatmap reveals intense, well-localized attention precisely over the tumor region, with minimal activation in surrounding healthy tissue. This spatial correspondence indicates that YOLOv8 has learned to prioritize salient pathological features. Such localization capability is valuable in real-world MRI settings, demonstrating the model's robustness to variations in imaging protocols, scanner specifications, and common artifacts. By focusing on the actual tumor regions, the model is less likely to be misled by irrelevant patterns in the data, making its predictions more reliable across institutions and patient groups.

From a clinical and ethical perspective, these interpretability findings are critical. High-performing models that lack transparent and anatomically aligned reasoning pose significant challenges for clinical trust. Reliance on such "black-box" systems particularly in brain tumor diagnostics can lead to delayed diagnoses or inappropriate clinical decisions. In contrast, the clearer localization exhibited by YOLOv8 facilitates safer integration into clinical workflows by supporting human-in-the-loop deployment, allowing radiologists to verify that AI predictions focus on meaningful tumor regions and exercise informed oversight. This is essential for ensuring patient safety, maintaining clinical accountability and mitigating the risks associated with fully automated decision-making.

VI. CONCLUSION AND FUTURE WORK

This paper presented a comparative analysis of two deep learning approaches namely, CNN and YOLOv8 for brain tumor classification using the BR35H MRI dataset in resource-constrained settings. Both models demonstrated strong detection capability, where YOLOv8 obtain a superior performance with 0.998 accuracy, 0.997 precision, 1.00 recall, and 0.998 F1-score. Its superior performance reflects its enhanced feature extraction capability and efficient architectural design, which appears more robust in distinguishing between tumor and non-tumor classes. The confusion matrix analysis further confirmed these observations, as YOLOv8 produced fewer misclassifications than the CNN model. The YOLOv8 model exhibited a substantial reduction in false negatives, an essential performance criterion for early and reliable tumor detection. This is particularly important from a clinical and patient-care perspective, as missed tumor cases can lead to delayed diagnosis, postponed treatment initiation, and potentially poorer health outcomes. By minimizing false negatives, YOLOv8 helps ensure that patients receive timely medical attention, which is critical for improving prognosis and overall survival rates. These results further indicate that YOLOv8 is a more reliable candidate for real-world deployment, particularly in diagnostic support systems where minimizing missed detections is crucial.

Despite the promising, near-perfect results obtained on the tested dataset, these findings may not fully reflect performance in real-world clinical settings, where MRI data are typically more heterogeneous and may include variations arising from different scanners, imaging protocols, noise, artifacts or rare tumor variants. Several limitations therefore remain to be addressed in future work. While this study focused on binary classification, extending the evaluation to multi-class tumor types such as meningioma, glioma, and pituitary tumors would enable a more clinically meaningful and comprehensive assessment. Although YOLOv8's ability to minimize false negatives (FN) highlights its potential as a reliable tool for early and clinically sensitive tumor detection, ethical and safety considerations must be carefully addressed to mitigate the risks associated with over-reliance on automated diagnosis. In particular, future research should emphasize the integration of human-in-the-loop frameworks, where AI systems function as decision-support tools that complement and assist expert radiologists. Further validation using diverse, multi-institutional datasets, cross-dataset evaluation, and experiments with multiple random seeds or k-fold cross-validation would provide a more thorough assessment of model consistency and reliability, thereby strengthening the generalizability and robustness of both CNN and YOLOv8 models. In addition, future studies could explore more advanced architectures, such as Vision Transformers (ViT) or hybrid CNN Transformer models in higher-resource environments, as well as lightweight adaptations of these architectures for deployment in resource-constrained clinical settings.

ACKNOWLEDGMENT

Special thanks to Kulliyyah of Information and Communication Technology, International Islamic University Malaysia and Faculty of Computer Science and Information Technology, University of Malaya for providing support and resources.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

AUTHOR(S) CONTRIBUTION STATEMENT

All authors contributed equally to this work.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ETHICS STATEMENT

This study did not require ethical approval

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