Volume 5, Issue III, March, 2026; No. 84, pp. 1068-1078
Submitted 2/12/2025; Final peer review 27/3/2026
Online Publication 2/4/2026
Available Online at http://www.ijortacs.com

BRAIN TUMOR IMAGE (BTI) DETECTION AND CLASSIFICATION USING AN ENHANCED YOLO-V8 ARCHITECTURE

[1]Okeke O.C., [2]Ibeonu O. C.
[1,2]Department of Computer Science; Chukwuemeka Odumegwu Ojukwu University,
Uli, Anambara State, Nigeria
Author Email: [1]ogoookeke@yahoo.com, [2]ogoodichik@gmail.com
[2]Corresponding Author's Email: ogoodichik@gmail.com

Abstract

Brain tumours have been known to be detected early and accurately as a constituent of effective clinical intervention and better patient survival. Nevertheless, the current diagnostic systems based on medical imaging have difficulties with the detection of heterogeneity of tumours, tumour size, dynamic growth, and the lack of labelled clinical data. This paper suggests a better deep transfer learning model to detect and classify brain tumour images (BTI) with a modified You Only Look Once Version 8 (YOLOv8) model. The proposed model combines Bi-Directional Feature Pyramid Network (Bi-FPN) to build a better multi-scale fusion of features, a Proposed Feature Optimizer (PFO) to build a better discriminative feature representation and an extra P2 detection layer to build a better sensitivity to small and early-stage tumours. A mixed dataset of clinical MRI data of the University of Nigeria Teaching Hospital (UNTH), Enugu, and a publicly available Kaggle brain MRI dataset of 7,243 images of four classes (glioma, meningioma, pituitary tumour, and no tumour) were used to train and evaluate the system. Pre-trained weights were used in transfer learning to overcome the problem of data scarcity and enhance generalisation. Performance on the model was evaluated based on standard evaluation measures such as precision, recall, mean Average Precision (mAP) as well as loss measures. Using experimental outcomes, it is proven that the enhanced YOLOv8 model is much better in comparison with the initial YOLOv8 framework, having a precision of 0.98, recall of 0.95, mAP50 of 0.98, and mAP5095 of 0.54, as well as lower localization and classification losses. These results show that there is improved robustness, accuracy, and reliability of brain tumour detection and classification. The suggested system is practical and scalable in early brain tumour screening and has high chances of being incorporated into the real clinical diagnostic systems.

Keywords: Brain Tumor Detection; Medical Image Analysis; Deep Transfer Learning; YOLOv8; MRI Imaging.

1. INTRODUCTION

Over the years, many studies have been submitted to diagnose this primary Brain Tumor Image (BTI) as a major type of neuropathic disorder. Traditional methods to solve the problem include biopsies, surgeries, autopsies, medical imaging, and analysis to identify abnormalities in the brain cells. However, medical imaging has evolved as a promising technique that facilitates early detection of BTI. According to Deborah et al. (2022), early detection of BTI is a vital and fundamental step that facilitates better management. Mahmud et al. (2023) posited that primary

BTI is very small and grows over time, hence early detection is an essential point for starting diagnostic plans and hence improving the chances of patient survival.

According to Sharif et al., (2020), medical imaging is the application of specialized machines to capture data modeling the internal parts of a body for visualization by an expert and analysis. It consists of several types which include: computed tomography (CT), Ultrasound, Magnetic Resonance Imaging (MRI), X-ray imaging, and Radiographic imaging. In Hussain (2021), the innovation of deep learning has revolutionized the application of medical imaging analysis in the healthcare sector. Deep learning is a type of convolutional neural network that specializes in solving image classification problems (ZainEldin, et. al., 2023). It involves a series of neural networks, interconnected to learn the intricate features of image pixels and then solve classification problems. However, Zahid et al. (2022), identified limited data availability and demand for huge data size as major constraints against the success of deep learning models and hence present the need for Pre-Trained Models (PTMs).

PTM is already trained deep learning algorithms with a large corpus of datasets and generates a model transferable (Aamir et al., 2022). These PTMs are adapted to other types of image classification problems, and as consistently recorded high overall performance. PTMs are of various types which include Alex.net, Mobile.Net, Res.Net, Google Net, YoloV, NasNet, Xception, DenseNet, and VGG (Qodri, et. al., 2021; Misu., 2023; Mahmud et al., 2023). In the context of neuropathology, PTM has evolved as a trending technique for the generation of models that facilitate the early detection of BTI.

For instance, Zahid et al. (2022) applied a Residual Network (ResNet) for the classification of BTI. Mahmud et al. (2023), compared ResNet-50, inceptionV3, and VGG-16 for the classification of BTI. Albanki and Mattar (2023) trained the CoAtNet model for BTI classification, while Al-Azzwi and Nazarov (2023) compared VGG19, Inception v3, and ResNet 101 for the classification of BTI. EfficientNet, LeNet-5, and AlexNet were trained in Al-Zoghby, et. al. (2023), for the BTI classification, while Rasool, et al. (2023), applied SqueezeNet for the early detection of BTI; while these studies have all made a significant contribution to the early detection and classification of BTI, Rabah et al. (2023) argued that the complexity, and heterogeneity of BTI remains a major challenge, another issue is the inconsistencies in classification outputs, and also lack of model validation with real-world BTI data, which collectively raises issues of reliability in the existing systems. In the context of heterogeneity, BTIs are very small in size, and dynamic, because their shapes change with time as the tumor grows (Seliger et al., 2022), these varying behaviors have remained a critical issue affecting the performance of existing deep transfer learning-based classification models. Therefore this research is aimed at developing an improved deep transfer learning framework capable of classifying dynamic BTI problems, to facilitate early detection of the disease and save life of patients.

2. THE PROPOSED SYSTEM DESIGN

In the proposed system for BTI classification, a deep transfer learning approach is proposed using the You Only Look Once (YOLO) Version 8 (YOLOV-8) algorithm. According to Misu (2023), the YOLOV series is the best when solving classification problem that involves precision in decision making. YOLO is a transfer learning algorithm that has recently continued to dominate the scientific community as the algorithm. YOLOv8 is a state-of-the-art object detection model that has demonstrated exceptional performance in accurately identifying and localizing objects in images. It is used in this work because it allows the model to quickly adapt to the specific task

of BTI classification, often achieving higher accuracy compared to training other deep learning models from scratch on a limited dataset. Additionally, the YOLOv8 enables efficient use of the limited medical imaging data available for BTI, as it allows the model to converge faster and generalize better to unseen data, which is crucial for real-world medical applications.
The method of the proposed system involves steps such as data collection, YOLOV-8, training of the YOLOV-8, model for classification, system integration, and system deployment. The main components of the YOLOV-8 are the input layer, backbone, neck, and head, as in Figure 1.

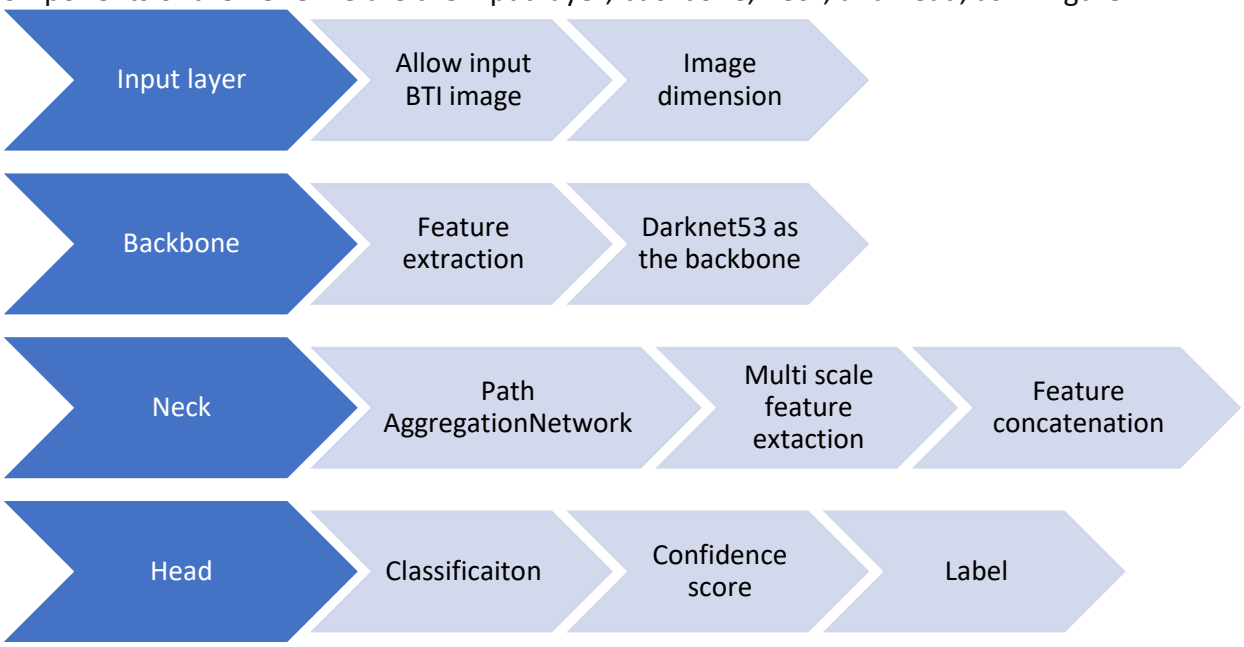

Figure 1: The hierarchical diagram of YOLOV-8
The YOLOV-8 is made of four main components which are the input layer, responsible for the dimensioning of the input image of BTI, the backbone which houses the Cross Stage Partial (CSP) Darknet53, which is a pre-trained model made of several convolutional layers, and applied as the backbone for the feature convolutional scan process. The neck is composed of the PAN, which enables the multiscale feature extraction process and then concatenates for training. The head is responsible for generating the BTI model for classification, including labels and confidence levels.
Figure 2 presents the block diagram of the proposed system. The first data model which considers the diverse characteristics of BTI is considered. The dynamic characteristics of brain tumors, including meningioma, glioma, and pituitary tumors, encompass their varied presentations across orientations of axial, coronal, and sagittal planes. Meningiomas, for instance, display distinct growth patterns in these orientations, impacting their diagnosis and treatment planning. Similarly, gliomas, with their invasive tendencies, can exhibit changes in size and shape across these planes over time, posing challenges for clinicians in managing their progression. Pituitary tumors, influenced by hormonal regulation, can manifest within the axial, coronal, and sagittal orientations, necessitating precise imaging interpretation and treatment strategies. Recognizing these dynamic features across different planes is paramount for accurate diagnosis, effective treatment, and ongoing monitoring of patients with brain tumors, ensuring optimal outcomes and quality of care. The data collected will be augmented to

Corresponding Author Tel: +2348160258696

improve the size and address issues of over-fitting before training YoloV-8 to generate the model for BTI detection and classification. When the YOLOV-8 receives the data, it first extracts the features at the backbone and then applies the path Aggregation Network (PANET) for multi-scale feature extraction in the neck, before the training process begins. During the training operation, the neurons will be optimized until the loss is tolerable, and then the model for the classification of BTI is generated. To test the model, data of BTI will be loaded to the trained model and the classification outcome will be returned. Figure 2 presents the block diagram of the proposed BTI classification model.

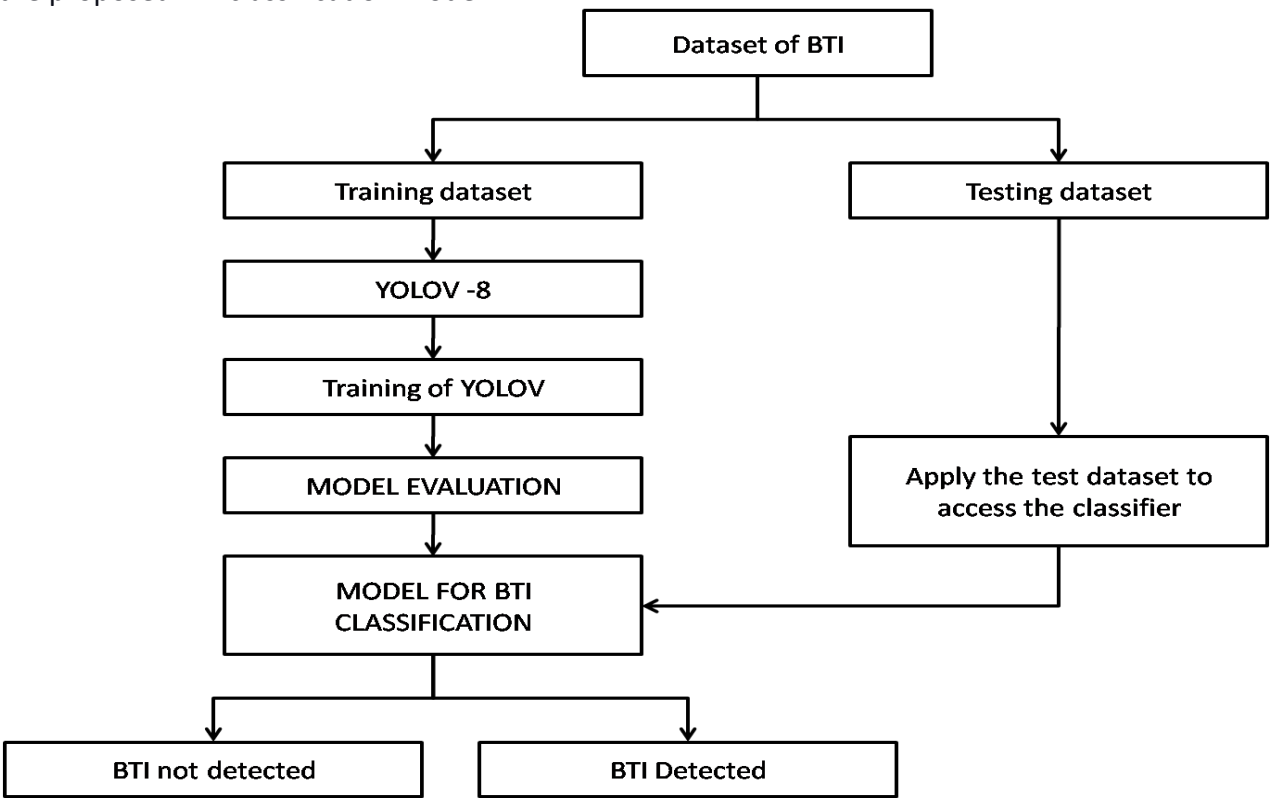

Figure 2: Block diagram of the proposed system

Figure 2 presents the proposed system block diagram. First, the dataset collected is duplicated into training and test datasets. The training dataset is loaded into the YOLOV8 and then trained to generate the model for BTI classification after evaluation. The test dataset is then applied to evaluate the model generated which will then be capable of classifying BTI and non-BTI images.

2.1 Data Acquisition

The data used for this project was collected from the University of Nigeria Teaching Hospital (UNTH), Enugu State, Nigeria, as the primary data source. To capture the dynamic brain tumor characteristics during data collection, a multi-dimensional approach was employed. The dataset includes information from 500 patients diagnosed with brain tumors over five years (2018–2023) and also those healthy, representing diverse demographics such as age, gender, occupation, and geographic location. Patients ranged in age from 10 to 80 years, ensuring coverage of both pediatric and adult populations, and enabling analysis of tumor characteristics across different life stages. The dataset encompasses various tumor types, such as gliomas, meningiomas, pituitary adenomas, and no tumors, categorized into stages (Grade I to Grade IV). Advanced imaging and diagnostic tools, such as MRI machines, were utilized to capture high-resolution

details, while techniques like functional MRI (fMRI) and diffusion tensor imaging (DTI) provided insights into tumor dynamics, including growth and infiltration patterns. The total dataset comprises over 220 imaging scans, along with clinical and demographic records, providing a comprehensive foundation for analysis. This formed the primary data source. The secondary data source is the Kaggle repository, which contains 7023 images of human brain MRI images which are classified into 4 classes: glioma, meningioma, no tumor, and pituitary. The total sample size of data collected is 7243 images spanning four classes.

2.2 The proposed Improved YOLOv8 for Brain Tumor Detection

The YOLOv8 architecture has undergone several enhancements to improve its performance for brain tumor detection, addressing limitations in its ability to handle multi-scale features, occlusions, and subtle tumor characteristics. The core improvements focus on enhancing feature extraction, boosting detection accuracy, and making the framework more robust for medical imaging tasks. The improvements are as follows:

1. Integration of Bi-Directional Feature Pyramid Network (Bi-FPN): One of the key improvements in this YOLOv8 modification is the integration of Bi-FPN, which refines the multi-scale feature fusion process. Traditional PANet (Path Aggregation Network) has limitations in efficiently fusing features from multiple scales. The Bi-FPN overcomes this by introducing lateral connection paths that help preserve low-level features while integrating them into deeper layers. This is particularly beneficial for brain tumor detection, where various tumor types and stages can present at different scales, requiring the framework to handle complex feature hierarchies effectively.

2. Proposed Feature Optimizer (PFO): Another major upgrade is the introduction of PFO after the SPPF layer. The PFO module improves feature map representation by condensing information along the channel dimension using GAP. This compact representation enhances the identification of key tumor features, especially in regions with low pixel density, such as partially occluded or early-stage tumors.

3. P2 Layer Integration for Faster Detection: The addition of the p2 layer and an expanded detection head improves the speed and accuracy of tumor classification. By increasing the feature map size and streamlining the convolutional process, the framework can quickly process high-resolution medical images while maintaining the fidelity of tumor details.

These combined upgrades make the improved YOLOv8 architecture particularly suited for brain tumor detection, as it can better handle complex, multi-scale tumor features and occlusions, providing faster and more accurate results in clinical settings. Figure 3 presents the improved YOLOV-8.

2.3Setup and Training of the Improved YOLOv8 for Brain Tumor Detection

The setup and training of the improved YOLOv8 framework for brain tumor detection involved several critical steps to optimize the framework for medical imaging applications. First, the environment was configured to support the deep learning model. This included setting up Python (version 3.8), installing essential deep learning libraries such as PyTorch, OpenCV, NumPy, and Matplotlib. GPU support, preferably with CUDA, was also ensured to accelerate training. Once the environment was prepared, the next step involved preparing the dataset, which consisted of MRI and CT scan images, along with corresponding annotation files. For the YOLOv8 model, the data was formatted in the YOLO annotation style, which included class IDs, coordinates, and dimensions of bounding boxes around the brain tumors in the images. The dataset covered various tumor types, such as gliomas, meningiomas, pituitary adenomas, and metastatic tumors, with different grades ranging from Grade I to IV.

After data preparation, a custom configuration file for YOLOv8 was created, specifying paths to the training and validation datasets, image sizes, and batch sizes. A key part of this process was defining the number of tumor classes (four in this case) and their corresponding names. The framework was initialized with pre-trained weights from a general object detection dataset, such as COCO, and was further trained on the brain tumor dataset. During the training process, the dataset was fed into the model for a set number of epochs, with hyperparameters such as learning rate, batch size, and image size being adjusted to achieve optimal performance. After training, the framework was evaluated using the validation dataset to assess its accuracy and ability to detect various types and grades of brain tumors. The enhanced YOLOv8 architecture, featuring the SPPF layer and Bi-directional PAN, significantly improved detection accuracy, particularly in identifying tumors at different scales and with occlusion, making it a robust solution for brain tumor detection in medical imaging.

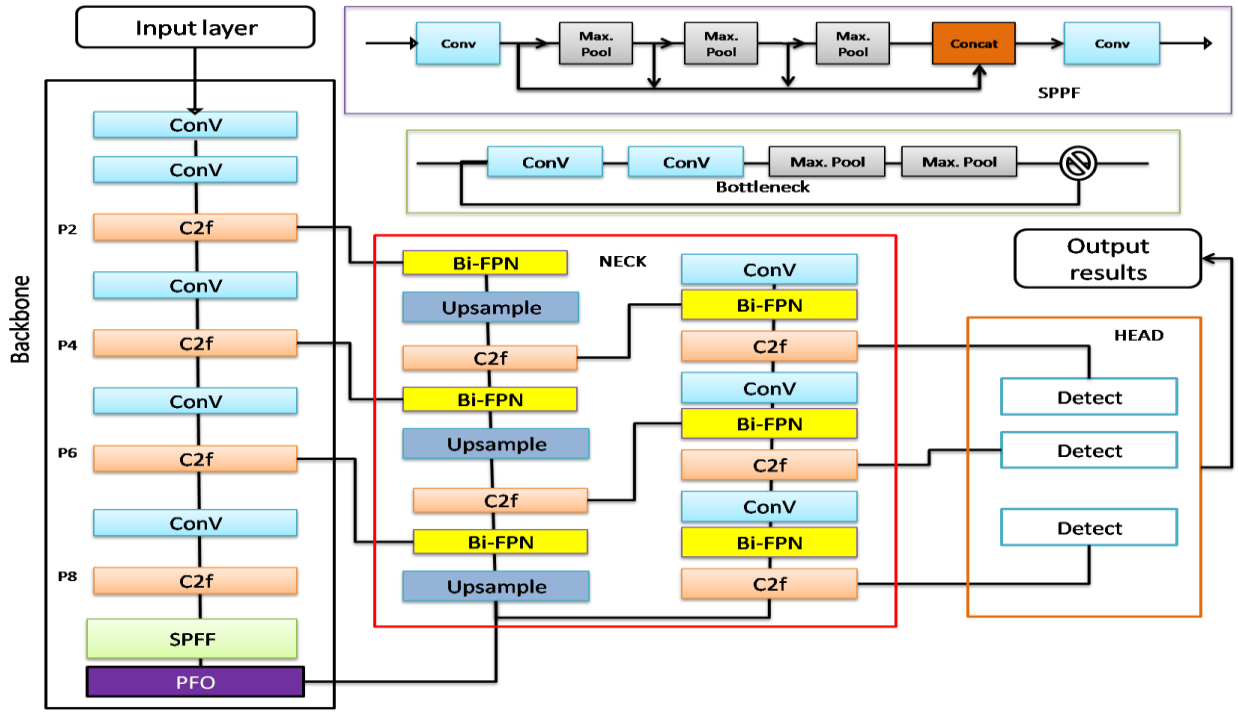

Figure 3: The improved YOLOV-8 Architecture

2.4 System Implementation of the Brain Tumor Classifier

The implementation of the brain tumor classifier involves integrating the YOLOv8 architecture with a custom dataset of MRI and CT scan images. The first step in the implementation is setting up the environment, ensuring that Python, PyTorch, OpenCV, and other necessary libraries are installed. A GPU with CUDA support is also configured to accelerate the training process. Once the environment is ready, the dataset consisting of brain tumor images is gathered, ensuring that each image is annotated with the correct bounding box coordinates and tumor class labels. The dataset is then split into training, validation, and test sets to facilitate proper model evaluation.

The YOLOv8 model is initialized with pre-trained weights from a general object detection dataset to leverage transfer learning. The model's configuration is customized to accommodate the specific dataset, including defining the number of tumor classes and their corresponding labels. Hyperparameters such as learning rate, batch size, and image size are optimized to achieve the best performance. During training, the model learns to detect various types of brain

tumors, including gliomas, meningiomas, pituitary adenomas. The training process continues over several epochs, refining the model's accuracy. After training, the model is evaluated on the validation dataset to assess its performance in terms of detection accuracy and robustness.
In the post-processing stage, techniques such as Non-Maximum Suppression (NMS) are applied to remove redundant bounding boxes and ensure the final detection results are accurate and distinct. The trained model is then tested on unseen data to evaluate its real-world performance. The final system output consists of images with bounding boxes around the detected tumors, providing clear visual results for medical practitioners to assess. This system is designed to be flexible and scalable, allowing for integration into healthcare workflows and continuous improvement with new data.

3. RESULTS

This section presents the result of the improved YOLO-8 training of the brain tumor dataset. The Figure 4 presents the training result of the traditional YOLOV8, while Figure 5 presented the result of the improved YOLOV-8. The performances were evaluated using accuracy, loss, mean absolute precision and recall. Figure 5 presents the results from the YOLOv8-based brain tumor classifier, showing the performance of the model during training and validation. The bounding box loss for training was 1.3, while for validation, it was 1.7. This indicates that the model performs well in localizing the tumor during training, though its ability to generalize on unseen data (as measured by validation) is slightly lower. The classification loss was 1.2 for both training and validation, suggesting that the model's ability to correctly classify the brain tumor remained consistent across the training and validation datasets.

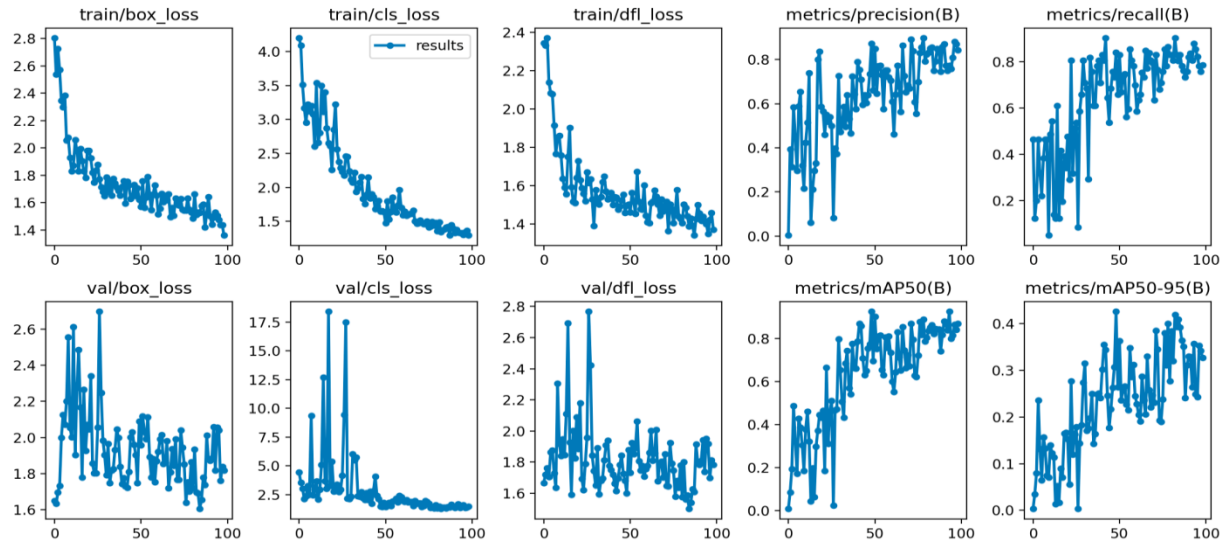

Figure 4: Result of the Traditional YOLOV8

Additionally, the focus loss, which measures how well the model focuses on the important features, was 1.2 during training and 1.7 during validation, showing a slight decline in focus when applied to new data.In terms of performance metrics, the classifier achieved a precision of 0.85, meaning that 85% of the tumor predictions made by the model were correct. The recall was 0.75, indicating that the model identified 75% of the actual brain tumors present in the images. The mAP50, which measures the average precision at an Intersection over Union (IoU) threshold of 0.5, was reported at 0.8, showing that the model was able to accurately detect tumors with a relatively high level of precision. However, the mAP50-95, which calculates the average

precision across multiple IoU thresholds (from 0.5 to 0.95), was reported at 0.34, suggesting that the model's performance was less robust when evaluated across a wider range of IoU thresholds. These results indicate that the model performs well in detecting and classifying brain tumors but could benefit from further optimization to improve generalization and precision across all IoU thresholds.

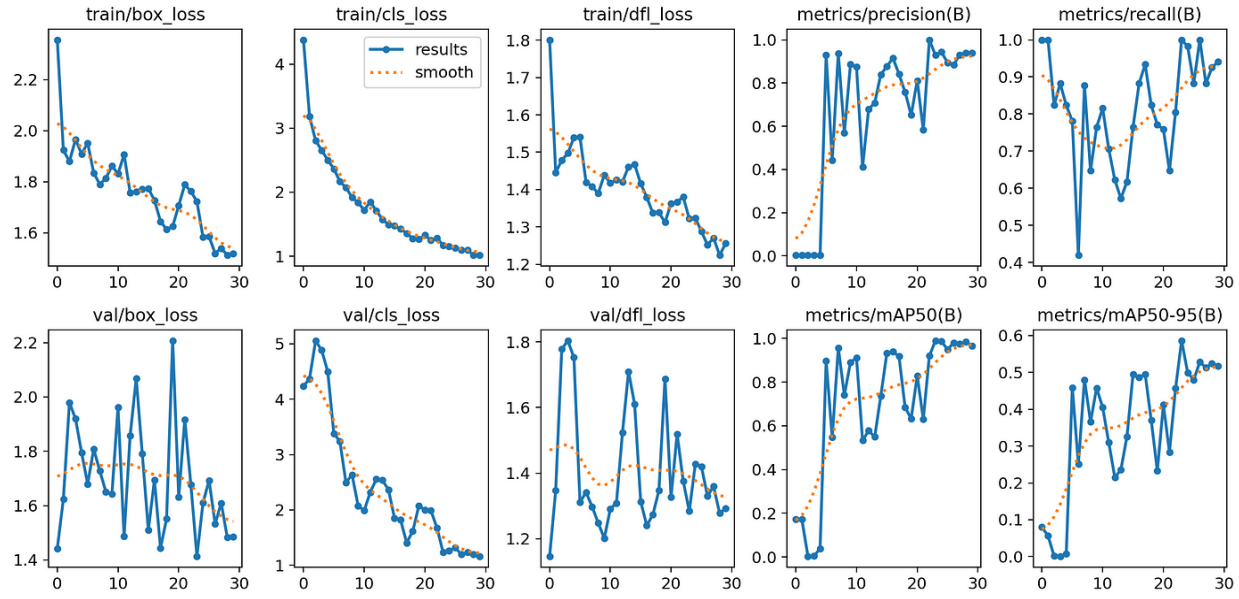

Figure 5: Result of the Improved YOLOV-8

Figure 5 presents the results of the improved YOLOv8-based brain tumor classifier, highlighting significant improvements in performance compared to the previous model. The bounding box loss during training is 0.8, which is a marked improvement over the previous model's 1.3, indicating better accuracy in localizing brain tumors. The validation bounding box loss is 1.5, slightly higher than the training loss, but still lower than the previous model's validation loss of 1.7. This suggests improved generalization and localization performance on unseen data. The classification loss during training is 1.1, which is slightly better than the previous model's 1.2, while the validation classification loss remains the same at 1.1, indicating consistent classification performance between training and validation datasets.The focus loss during training is 1.3, slightly higher than the previous model's focus loss of 1.2, which may suggest that while the model is focusing on the tumor region, there may still be room for improvement in its attention to critical features. However, this value does not significantly impact overall performance. The precision of the improved model is 0.98, a substantial improvement over the previous model's 0.85, meaning that 98% of the model’s predicted tumors are correct. The recall is 0.95, indicating that the improved model correctly identifies 95% of the actual tumors, an improvement over the previous recall of 0.75. The mAP50, at 0.98, also shows a significant boost compared to the previous model's 0.8, demonstrating that the improved model achieves high precision in detecting tumors across various IoU thresholds. The mAP50-95 is 0.54, which is an improvement over the previous value of 0.34, showing that the model performs better across a broader range of IoU thresholds. Overall, these results highlight the improved YOLOv8 model's enhanced ability to detect and classify brain tumors with greater accuracy and reliability.

Corresponding Author Tel: +2348160258696

Comparative analysis of the YOLOv8 and improved YOLOv8 results for the brain tumor classifier is presented in Table 1:

Table 1: Comparative Analysis of the two Results

Metric	YOLOv8 (Original)	Improved YOLOv8
Bounding Box Loss (Training)	1.3	0.8
Bounding Box Loss (Validation)	1.7	1.5
Classification Loss (Training)	1.2	1.1
Classification Loss (Validation)	1.2	1.1
Focus Loss (Training)	1.2	1.3
Focus Loss (Validation)	1.7	1.3
Precision	0.85	0.98
Recall	0.75	0.95
mAP50	0.8	0.98
mAP50-95	0.34	0.54

Table 1 presents the comparative results where the improved YOLOv8 model outperforms the original YOLOv8 framework across all key performance metrics, making it the better model for brain tumor classification. Firstly, the bounding box loss during training for the improved model is 0.8, which is lower than the original model's 1.3. This indicates that the improved model is more accurate in localizing brain tumors. Although the validation bounding box loss is 1.5 for the improved model compared to 1.7 for the original, it still suggests better generalization to unseen data. This shows that the improved model retains its localization ability even when applied to new data.

In terms of classification loss, the improved model performs better with a value of 1.1 for both training and validation, compared to the original model's 1.2. This indicates that the improved model is better at correctly classifying brain tumors, both during training and validation, resulting in fewer misclassifications. When evaluating focus loss, the improved model shows a slight increase in the training phase (1.3 vs. 1.2), but the validation focus loss is significantly lower (1.3 vs. 1.7). This suggests that while the improved model may have a marginally higher focus loss during training, it performs better in maintaining focus on critical tumor features during validation.

The improved model's precision of 0.98 and recall of 0.95 are both substantially higher than the original model's 0.85 and 0.75, respectively. This means that the improved model is more accurate in detecting tumors (higher precision) and identifies a greater percentage of actual tumors (higher recall), reducing both false positives and false negatives. These improvements indicate that the model is more reliable in its predictions.

Lastly, the improved model achieves a significantly higher mAP50 of 0.98, compared to 0.8 for the original model, demonstrating a substantial increase in precision at the 0.5 Intersection over Union (IoU) threshold. The mAP50-95 score of 0.54 for the improved model, which is much higher than the original model's 0.34, shows that the improved model performs better across a wider range of IoU thresholds, reflecting its superior overall detection capabilities.

In conclusion, the improved YOLOv8 model is the better choice, as it exhibits higher accuracy, precision, recall, and generalization, along with more robust performance across different evaluation metrics. These improvements make the improved model significantly more effective for brain tumor classification.

4. CONCLUSION

The study has provided a better deep transfer learning model on the detection and classification of BTIs on an improved YOLOv8 model. The study tackled some of the important issues of the current classification systems of brain tumours such as heterogeneity of tumours, small tumour size, dynamic growth patterns and unavailability of labelled medical imaging data. The proposed model, including Bi-Directional Feature Pyramid Network (Bi-FPN), a Proposed Feature Optimizer (PFO) and an extra P2 detectors layer, enhanced the multi-scale feature extraction and sensitivity to tiny tumour features. The system was trained and tested on a mixed dataset on the University of Nigeria Teaching Hospital (UNTH) and Kaggle, which consisted of four tumour classes namely glioma, meningioma, pituitary tumour and no tumour.

The experiment results proved that the enhanced YOLOv8 model was much better than the original YOLOv8 on the basis of all evaluation metrics. Lower bounding box and classification losses were obtained with the improved model, which results in a superior localization and classification of tumours. The precision (0.98), recall (0.95), mAP50 (0.98), and mAP50-95 (0.54) performance metrics ensured that the model was robust, capable of generalisation, and reliable in the detection of tumours of different sizes and in the different imaging conditions. This is what shows how effective the architectural enhancements were in addressing the complexity and dynamic nature of brain tumours in medical imaging.

To sum up, the brain tumour classification system enhanced with YOLOv8 is a promising solution offering high-quality and effective brain tumour detection and assistance in clinical decision-making. It is highly accurate and robust enough to be applied in the real-life healthcare setting, especially when using a small set of annotated data. The system can support radiologists by saving on the time of diagnosing as well as minimising human error. Further research can be aimed at verifying the model using larger multi-centric clinical samples, tumour segmentation, and grading, as well as adapting the system into practical clinical diagnostic systems to increase its clinical relevance.

REFERENCES

Aamir, M., Rahman, Z., Dayo, A. Z., Abro, A. W., Uddin, I. M., Khan, I., Imran, S. A., Ali, Z., Ishfaq, M., Guan, Y., & Hu, Z. (2022). A deep learning approach for brain tumor classification using MRI images. *Computers and Electrical Engineering*, *101*, Article 108105. https://doi.org/10.1016/j.compleceng.2022.108105

Al-Azzwi, N. H. Z., & Nazarov, A. N. (2023). Brain tumor classification based on improved stacked ensemble deep learning methods. *DOI:10.31557/APJCP.2023.24.6.2141*

Albanki, A. J., & Mattar, A. E. (2023). Classification of brain tumor using CoAtNet model. *American Journal of Biomedical Science & Research*. ISSN: 2642-1747.

Al-Zoghby, A. M., Al-Awadly, E. M. K., Moawad, A., Yehia, N., &Ebada, A. I. (2023). Dual deep CNN for tumor brain classification. *Diagnostics*, *13*, Article 2050. https://doi.org/10.3390/diagnostics13122050

Deborah U. Ebem, John C. Onyianta, Daniel O. Erhunmwunsee, &Chikaodili N. Ihudiebube (2022). Determining the predictive performance of hybrid classification algorithms on Covid-19 patient death rate in Nigeria. *International Journal of Mechatronics, Electrical and Computer Technology (IJMEC), 12*(44), 5191–5194. ISSN: 2305-0543 (Online), ISSN: 2411-6173 (Print).

Hussain A. (2021). Brain tumor detection in magnetic resonance imaging using deep learning approach [Preprint]. Research Square. https://doi.org/10.21203/rs.3.rs-2281460/v1

Mahmud, M., Mamun, M., & Abdelgawad, A. (2023). A deep analysis of brain tumor detection from MR images using deep learning networks. *Algorithms, 16*(4), Article 176. https://doi.org/10.3390/a16040176

Misu, S. R. (2023). Brain tumor detection using deep learning approaches [Bachelor's thesis]. Department of Computer Science and Engineering.

Qodri, N. K., Soesanti, I., & Nugroho, A. H. (2021). Image analysis for MRI-based brain tumor classification using deep learning. *IJITEE, 5*(1).

Rabah, N., Ait Mohand, F.-E., & Kravchenko-Balasha, N. (2023). Understanding glioblastoma signalling, heterogeneity, invasiveness, and drug delivery barriers. *International Journal of Molecular Sciences, 24*, Article 14256. https://doi.org/10.3390/ijms241814256

Rasool, M., Ismail, N. A., Al-Dhaqm, A., Yafooz, W. M. S., &Alsaeedi, A. (2023). A novel approach for classifying brain tumors combining a SqueezeNet model with SVM and fine-tuning. *Electronics, 12*, Article 149. https://doi.org/10.3390/electronics12010149

Seliger, C., Meyer, A.-L., Leidgens, V., Rauer, L., Moeckel, S., Jachnik, B., Proske, J., Dettmer, K., Rothhammer-Hampl, T., &Kaulen, L. D. (2022). Metabolic heterogeneity of brain tumor cells of proneural and mesenchymal origin. *International Journal of Molecular Sciences, 23*, Article 11629. https://doi.org/10.3390/ijms231911629

Sharif, M., Amin, J., Raza, M., Yasmin, M., & Satapathy, S. C. (2020). An integrated design of particle swarm optimization (PSO) with fusion of features for detection of brain tumor. *Pattern Recognition Letters, 129*, 150–157.

Zahid, U., Ashraf, I., Khan, A. M., Alhaisoni, M., Yahya, M. K., Hussein, S. H., &Alshazly, H. (2022). BrainNet: Optimal deep learning feature fusion for brain tumor classification. *Computational Intelligence and Neuroscience, 2022*, Article 1465173. https://doi.org/10.1155/2022/1465173

ZainEldin, H., Gamel, S. A., El-Kenawy, E.-S. M., Alharbi, A. H., Khafaga, D. S., Ibrahim, A., & Talaat, F. M. (2023). Brain tumor detection and classification using deep learning and sine-cosine fitness grey wolf optimization. *Bioengineering, 10*, Article 18. https://doi.org/10.3390/bioengineering10010018