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# DEEP TRANSFER LEARNING–BASED FRAMEWORK FOR AUTOMATED BRAIN TUMOR DETECTION, CLASSIFICATION AND SEGMENTATION USING THE YOLOV8 ARCHITECTURE

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**Abstract**

The presence of complex and heterogeneous tumour characteristics is still a decisive problem in the diagnosis of brain tumours that makes it a significant issue in neuropathology. It is necessary to detect early and properly along with effective planning of treatment and better patient survival. This study gives a comprehensive transfer learning framework of automated detection, classification, and segmentation of brain tumours using the YOLOv8 architecture. The proposed system will be able to address the dynamic neuropathic features to incorporate the real-time object recognition and enhanced features extraction and multi-scale learning functions. The model was trained and evaluated using a hybrid dataset of primary MRI data that was gathered in the University of Nigeria Teaching Hospital (UNTH), Enugu, and secondary data that was sourced in the Kaggle repository. The data was a collection of 7,243 MRI images divided into four classes in the form of glioma, meningioma, pituitary tumour, and no tumour. The system has been built with the help of the Extreme Programming (XP) in order to deal with the refinements and flexibility in an iterative way. Instead, transfer learning using the pre-trained YOLOv8 weights was used and the model was hyperparameter tuned and improved feature fusion methods. It was shown that the suggested YOLOv8-based model reached a precision of 0.85, recall 0.75, and a mean Average Precision (mAP50) of 0.80, which is a good result in the context of brain tumour detection and classification. The software system was integrated and it was able to provide real-time tumour localization, segmentation and labelling that generates clinical decision-making. The results show the usefulness of deep transfer learning in automated brain tumour detection and emphasise the possibilities of the proposed system as a useful diagnostic aiding tool in a healthcare setting.

**Keywords: Brain Tumor Detection; Neuropathology; Deep Transfer Learning; YOLOv8; Medical Image Classification**

## 1. INTRODUCTION

Neuropathology is the branch of medicine and pathology concerned with the study of diseases of the nervous systems such as the brain, spinal cord, and peripheral nerves (Lam et al., 2024; Ghosh et al., 2020). In Albanki and Mattar (2023), it encompasses the examination and analysis

of neural tissues to diagnose various neurological disorders such as lesions, tumors, infections, degenerative changes, and other pathological conditions affecting the nervous system.

Bernetti et al. (2021), classified neuropathic disease into four categories which are neurodegenerative diseases (such as Alzheimer's disease, Parkinson's disease, and amyotrophic lateral sclerosis), brain tumor infections (such as meningitis and encephalitis), vascular disorders (such as stroke and aneurysms), and congenital anomalies (such as heart disease) respectively; while a tangible number of literature have been submitted with solutions tailored towards the detection and management of these neuropathic diseases classes, the brain tumor class has continued to gain increased research attention this 21st century (Muhammad et al., 2022).

In Mahmud et al. (2023), a brain tumor is a collection of abnormal cells that develop in the inflexible skull enclosing the brain, and any expansion within the area can result in issues. It can also occur due to originating from another part of the body and then spreading over to the brain segment (Mahmud et al., 2023). Thakkar et al. (2020), revealed that in America, over 80,000 persons are diagnosed with brain tumors every year. In the same vein, the World Health Organization (WHO), reported that in the year 2020, Nigeria recorded over 50% increase in brain tumor cases, when compared to the previous year (WHO, 2020), while Tiwari et al. (2022) revealed that over 250,000 people are diagnosed globally with cases of brain tumor every year.

Many studies have applied deep learning for the classification of neuropathic diseases; one of the notable studies is Abdusalomov et al. (2023), who refined YOLOv7 to improve the detection of meningioma, glioma, and pituitary gland tumors, but despite the success, an adaptive model which can detect heterogeneity characteristics of neuropathic diseases has not been considered, and this remains the limitation.Therefore, this study is aimed at developing an improved deep transfer learning framework capable of classifying dynamic neuropathic problems, to facilitate early detection of the disease and save life of patients.

## 2. METHODOLOGY

The methodology used for the study is Extreme programming (XP). XP is an agile software development framework that emphasizes rapid iterations, continuous feedback, and close collaboration between developers and stakeholders. Given the iterative nature of the research process and the need to adapt to changing requirements, XP provides a flexible and responsive approach that aligns well with the objectives of the study. Moreover, the strong focus on communication and collaboration in XP fosters a productive working environment where researchers can share ideas, discuss challenges, and collectively work towards the research goals. Through the adoption of XP methodology, the study can benefit from its proven track record in delivering high-quality results in a timely and efficient manner, making it a suitable choice for this research endeavor.

### 2.1 Data Collection

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

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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 Propose a Transfer Learning Framework Capable of Medical Image Classification**

The proposed transfer learning framework is YOLOV-8. This YOLOV-8is designed for efficient real-time object detection. The model uses a single Convolutional Neural Network (CNN) to simultaneously perform both object localization (bounding box prediction) and classification. This is achieved through a sequence of layers that progressively extract and refine features from the input image. The architecture starts with an input layer, where the raw image is passed to the network. The input is then processed by convolutional layers (Conv), which extract lower-level features such as edges, corners, and textures. These convolutional layers progressively reduce the spatial dimensions of the input, while increasing the depth (number of channels) to capture more complex features at higher levels. The backbone of YOLOv8 comprises multiple C2F blocks (Cross-Stage Partial Networks), which are responsible for feature extraction. The C2F blocks split the input features into smaller parts, which are processed by bottleneck layers and then recombined. This helps the network capture both fine-grained local features and more global contextual information. After this, the SPPF (Spatial Pyramid Pooling Fusion) layer enhances multi-scale feature fusion, allowing the network to extract relevant features at different resolutions. The neck section of the framework refines these features further by using concatenation (Concat) layers, and upsampling layers, to combine and upscale low- and high-level features. Finally, the output layer produces detection results, including bounding box coordinates, object classification, and confidence scores for each predicted object. Figure 1 presents the architecture of traditional YOLOV-8.

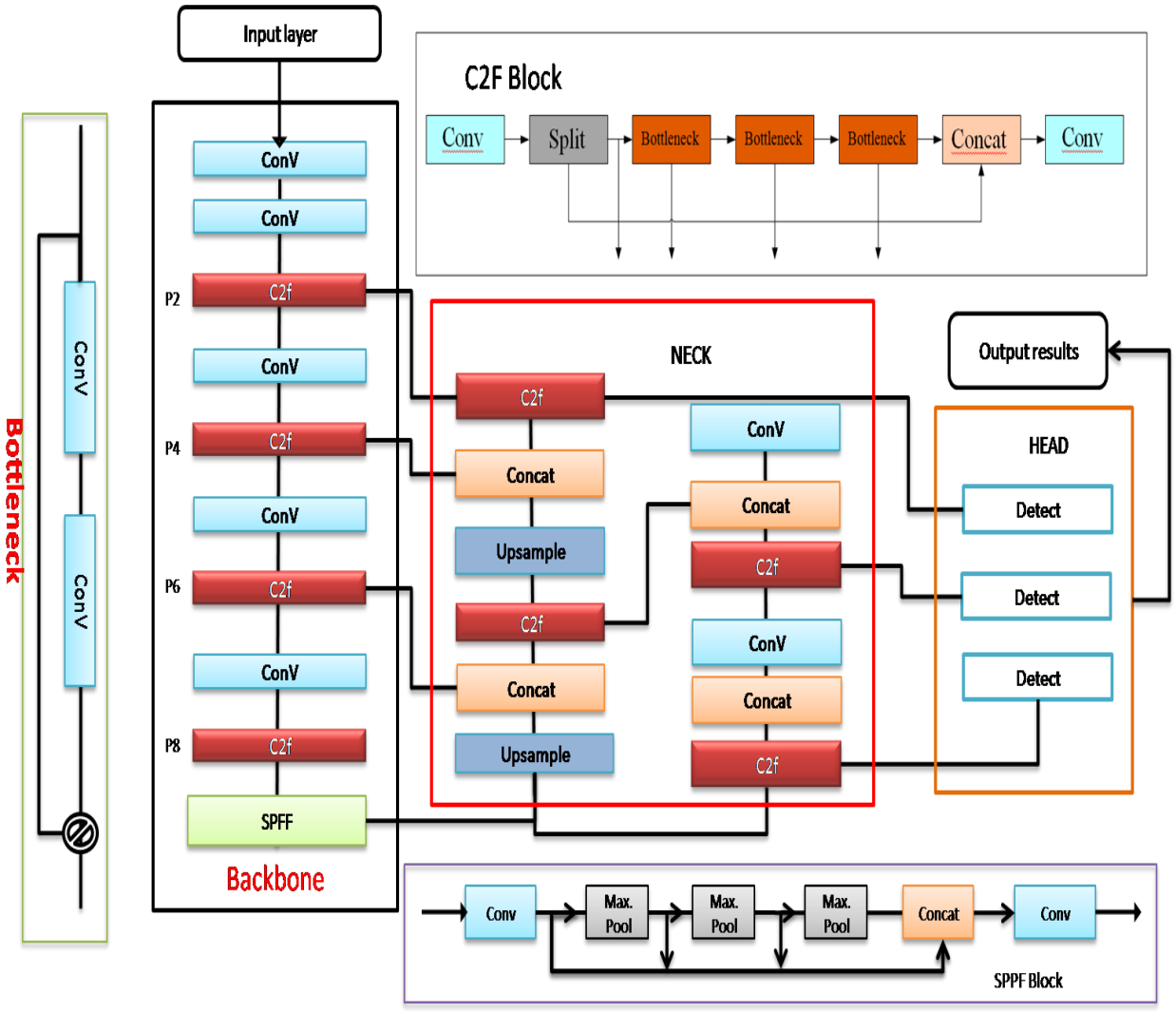


**Figure 1: Architecture of the YOLOV-8 model**

A detail analysis of the YOLOv8 Architecture in figure 1 is presented as follows.

1. Input Layer: The input image is fed into the network, where it is pre-processed to a fixed size, often 416x416 or 608x608, to standardize the input dimensions. This ensures consistency across all images during training and inference.

2. Convolutional Layers (Conv): These layers perform the initial feature extraction by applying convolutional filters to the input image. Each convolution layer detects specific features such as edges, colors, and textures, progressively building more complex feature representations as the layers increase in depth.

3. C2F Blocks (Cross-Stage Partial Networks): This block enhances feature extraction by splitting the feature map, processing different parts in parallel, and merging them back together. The bottleneck structure within C2F blocks reduces computation costs while retaining important features. These blocks also allow the network to maintain high performance by optimizing feature flow across different stages.

4. SPPF (Spatial Pyramid Pooling Fusion): The SPPF layer captures features at multiple spatial scales by applying different levels of pooling and concatenating the results. This allows YOLOv8 to process objects at varying sizes and resolutions, which is critical for accurate object detection in images that contain objects at different scales.
5. Neck (Concatenation and Upsample Layers): In the neck section, the network uses concatenation (Concat) layers to merge feature maps from different stages, combining high-level semantic features with low-level spatial information. Upsampling layers are applied to ensure that feature maps maintain high resolution, enabling the network to focus on small, detailed features in the image.
6. Output Layer: The final layer of YOLOv8 generates the output, which includes predicted bounding box coordinates for object localization, class probabilities for classification, and confidence scores indicating the certainty of the predictions. The model produces multiple bounding box predictions per image, from which the best ones are selected using techniques like non-maxima suppression.
This architecture, designed for real-time performance, enables YOLOv8 to achieve high accuracy while maintaining efficiency, making it suitable for tasks such as object detection in images and videos. However, for complex tasks like brain tumor classification, its general-purpose design may need to be adapted for more specialized feature extraction and classification. Algorithm 1 presents the stepwise implementation of the model for brain tumor detection

**Algorithm 1: YOLOv8-Based Brain Tumor Detection Algorithm**

1. *Start*
2. *Environment Setup: Install necessary libraries and enable GPU support with CUDA.*
3. *Data Input: Collect MRI scan images of brain tumors with annotations.*
4. *Dataset Preprocessing: Format the dataset into YOLO annotation style.*
5. *Dataset Split: Split the dataset into training, validation, and test sets.*
6. *Model Initialization: Initialize YOLOv8.*
7. *Hyper-parameter Tuning: Set learning rate, batch size, and image size for optimal training.*
8. *Model Training and Evaluation: Train the model and validate model performance.*
9. *Feature Enhancement: Apply PFO for multi-scale feature extraction.*
10. *Neck Enhancement: Implement Bi-directional PAN for better feature fusion.*
11. *Model Testing: Test the final model on unseen data to assess robustness and accuracy.*
12. *Model Generation: Generate the final trained model.*
13. *End*

**2.3 System Flowchart**

The system flowchart outlines the sequence of operations involved in the brain tumor detection process. It visually represents the steps from input image acquisition to output prediction as in Figure 2:

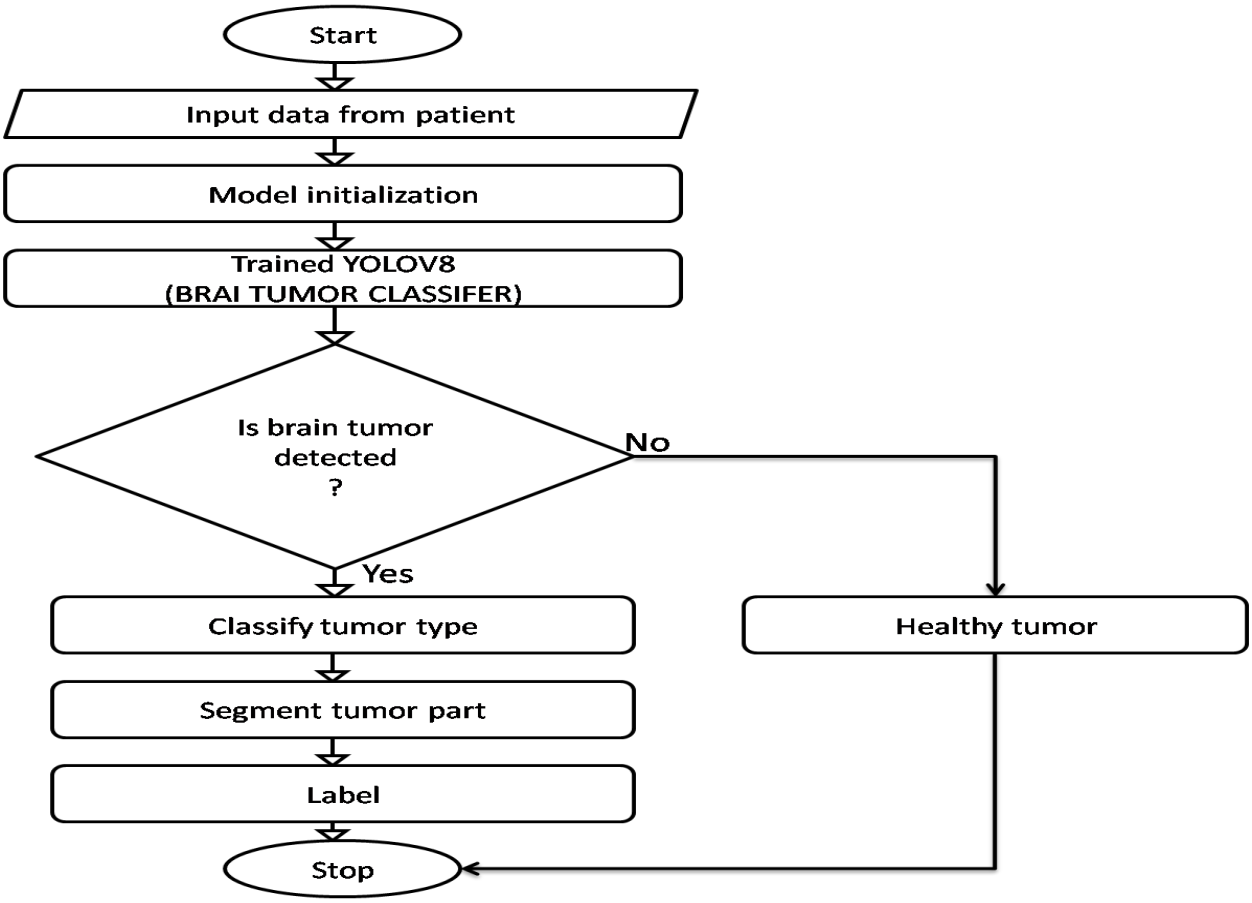


**Figure 2:** Brain tumor detection and classification flow chart

The flowchart outlines the operational workflow of the Brain Tumor Detection and Classification System, detailing the step-by-step processes involved in analyzing patient data to determine brain tumor presence and classification. The process begins with the Start node, which marks the initiation of the system. This is followed by the Input data from patient step, where data is uploaded into the system. The input typically includes brain imaging data, such as MRI scans, which are critical for tumor detection. The next step is Model Initialization, where the YOLOv8 (You Only Look Once version 8) model, specifically trained for brain tumor classification, is initialized. At this stage, the deep learning model is activated, and all its parameters are loaded to process the input data efficiently. Once the model is initialized, the system moves to the Trained YOLOv8 (Brain Tumor Classifier) stage.

Here, the YOLOv8 model analyzes the input data to detect the presence of a brain tumor. The system applies advanced feature extraction and detection capabilities of YOLOv8 to identify abnormal patterns in the brain images. The central decision-making step in the workflow is Is brain tumor detected? This decision point determines whether a tumor is present or not. If no tumor is detected, the process directs to the No tumor output, where the system confirms that the brain scan does not exhibit any abnormalities, and the workflow terminates. If a brain tumor is detected, the system proceeds to the next stages of analysis:

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1. Classify tumor type: The system categorizes the detected tumor into predefined types such as glioma, meningioma, or pituitary tumor. This classification helps in identifying the nature and severity of the tumor.
2. Segment tumor part: In this step, the system performs segmentation, which involves isolating the tumor region from the rest of the brain image. This step is crucial for accurately defining the boundaries and size of the tumor.
3. Label: The system labels the segmented tumor region and marks its position, often providing additional annotations like confidence scores and region of interest (ROI) details for medical interpretation.

Finally, the workflow ends with the Stop node, marking the completion of the process. At this stage, the system has successfully provided outputs such as tumor classification, segmentation, and labeling, or confirmed a healthy diagnosis.

**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. SYSTEM RESULTS**

This section presents the result of the YOLO-8 training of the brain tumor dataset. The Figure 3 presents the training result of the traditional YOLOV8. The performances were evaluated using accuracy, loss, mean absolute precision and recall.

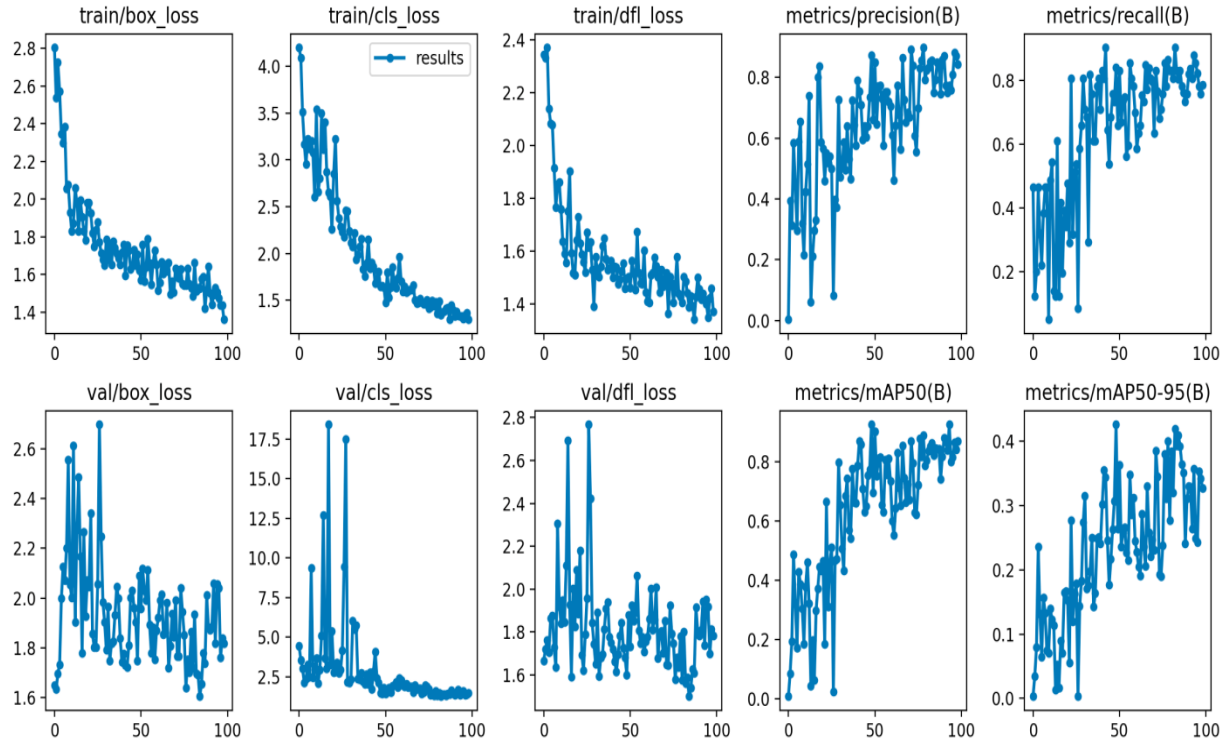


Figure 3: Result of the YOLOV8

Figure 3 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. 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.

The result of system integration was achieved using when the model was tested with real data collected from UNTH and then applied to test the developed software.

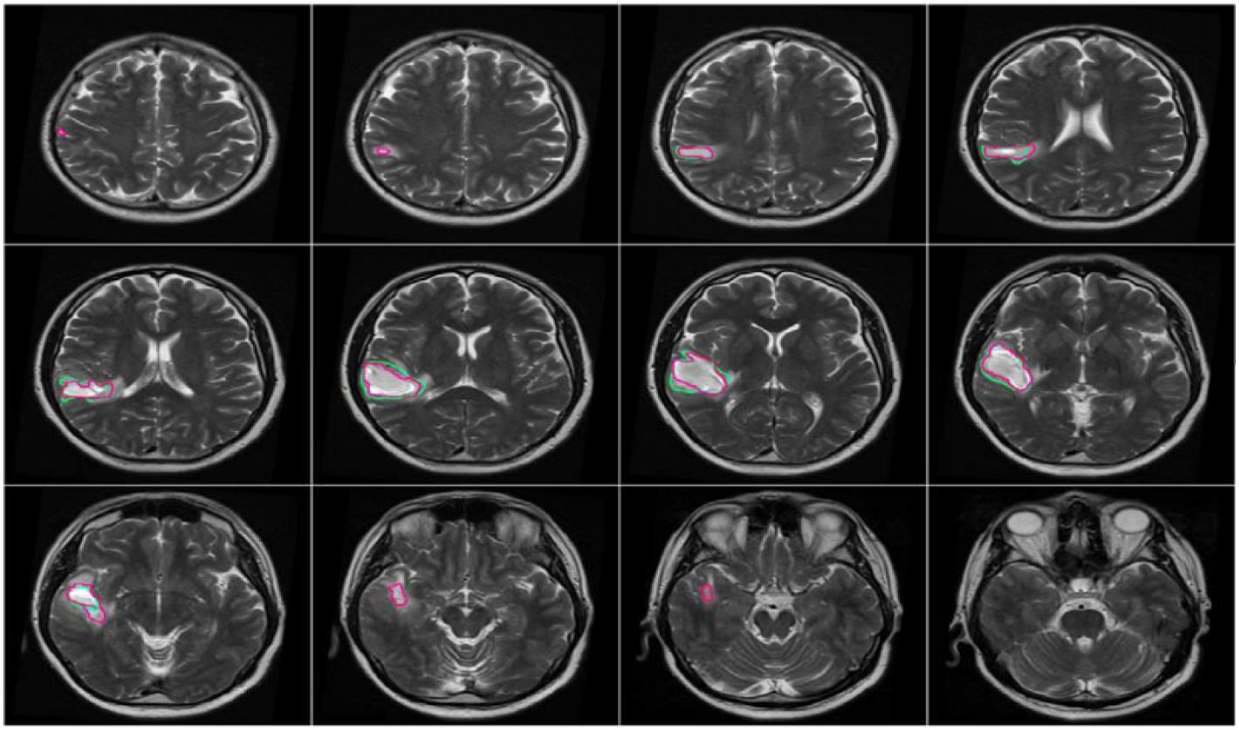

Figure 4: Presents the test data used to evaluate the software.

Figure 4 present the test data while Figure 5 presents the user interface data of the software for the detection of brain tumor.

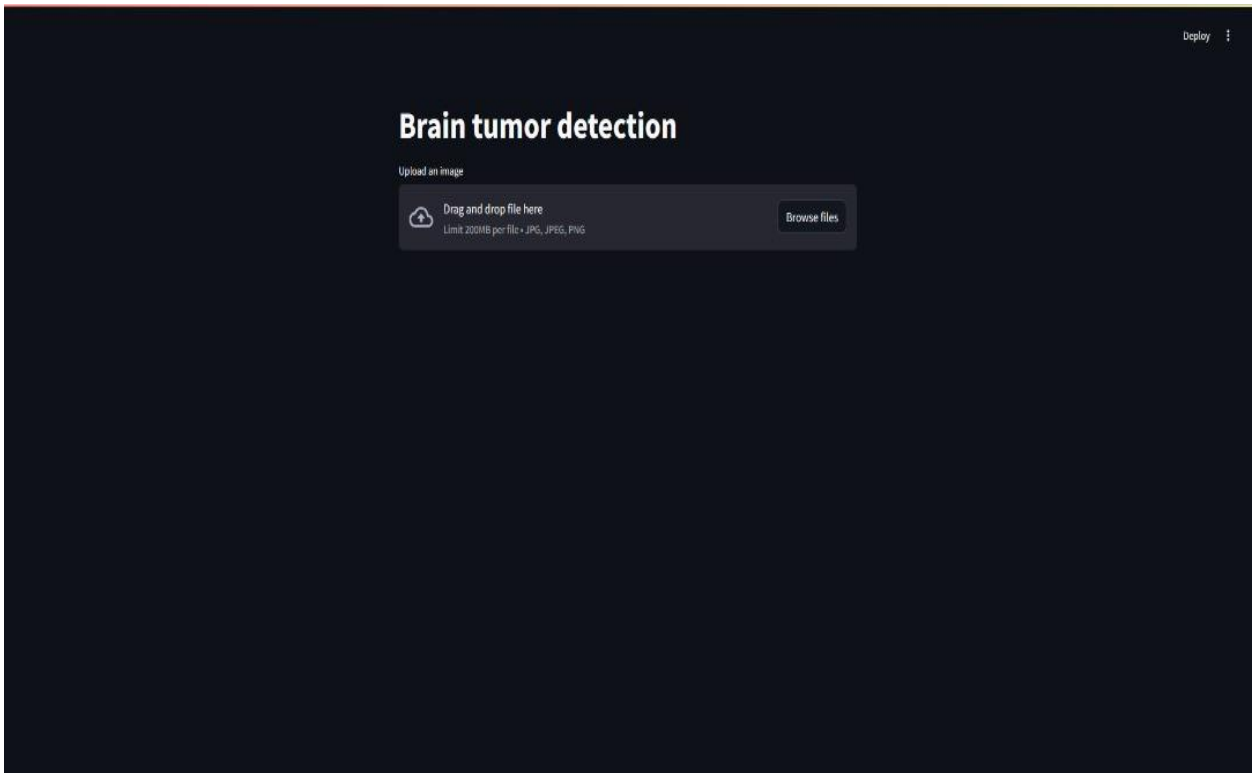


Figure 5: The integrated brain tumor classification software

Figure 5 presents the software interface developed for integrated brain tumor classification. The software was designed as a user-friendly platform to facilitate medical image analysis and classification, leveraging the deep transfer learning model developed in this research. The interface allows users, such as medical professionals, to upload brain tumor images for real-time detection and classification. Figure 6 presents the result of the data upload from the software.

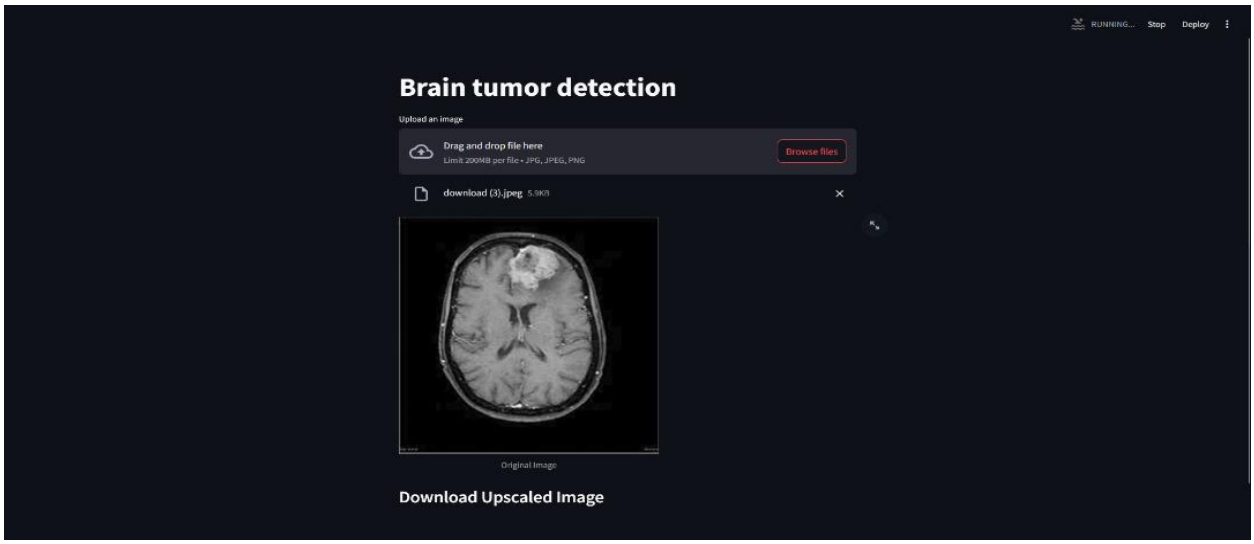


Figure 6: Result of the test data upload

Figure 6 presents the result of the test data upload within the integrated brain tumor classification software. It illustrates the functionality of the system in processing and analysing uploaded test images for tumor detection and classification. Figure 7 presents the classification result showing the classified image, segmentation of the tumor and label.

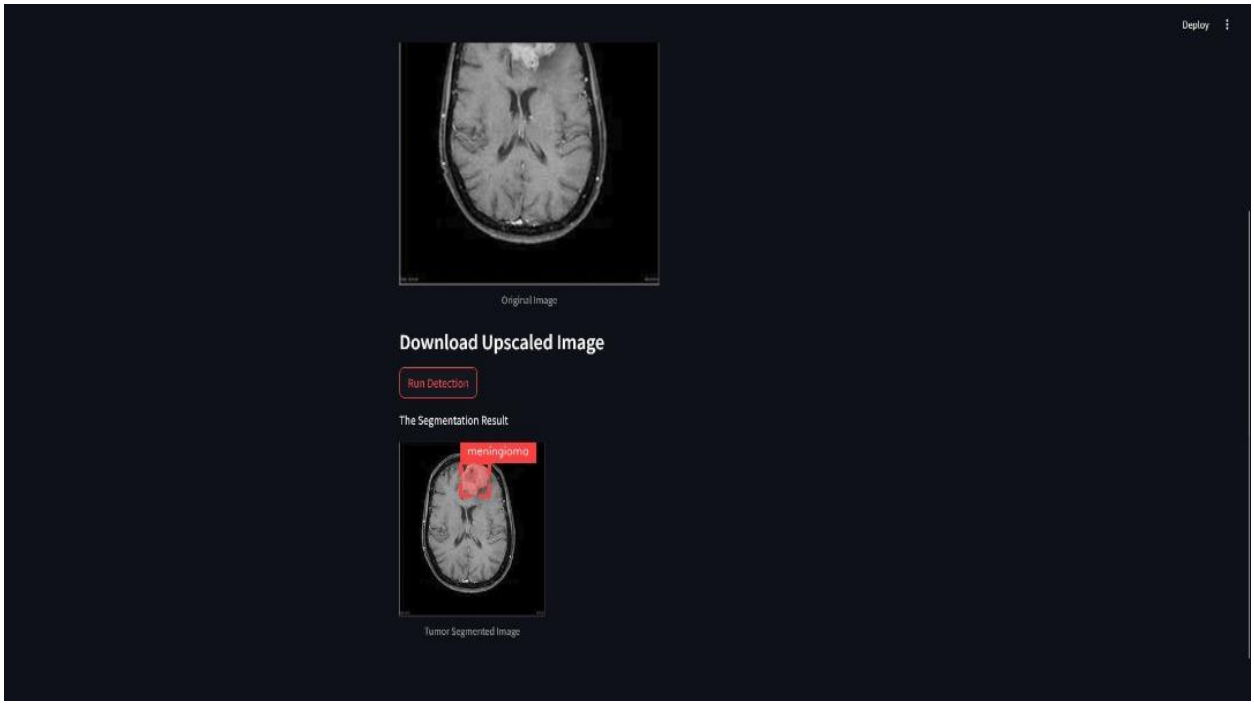

Figure 7: Result of the Classification, Segmentation and Label of Brain Tumor

Figure 7 presents the results of the classification, segmentation, and labelling of brain tumors using the integrated brain tumor classification software. It showcases the software's ability to perform advanced image analysis by not only detecting brain tumors but also segmenting the affected areas and labelling them with precise classifications.The classification process identifies the specific type of brain tumor present in the image and assigns a confidence score based on the YOLOv8 model's predictions. The segmentation feature delineates the boundaries of the tumor region within the brain scan, providing a clear visual representation of the affected area. Each identified tumor is labelled with its corresponding classification, such as tumor type and severity, enabling medical professionals to make informed decisions. This functionality demonstrates the enhanced capabilities of the system, integrating detection, segmentation, and labelling into a single streamlined workflow. The results emphasize the model's effectiveness in providing comprehensive diagnostic information, which is critical for planning treatment strategies and monitoring disease progression.

## 4. CONCLUSION

This study provided the construction of a better deep transfer learning framework to detect, classify, and segment brain tumours with the YOLOv8 model. The system was trained using both primary and secondary data on MRI, which is based on the data acquired via the University of Nigeria Teaching Hospital (UNTH) and on the secondary data on the same subject referenced in the Kaggle repository, respectively. The system was trained using four classes: glioma, meningioma, pituitary tumour, and no tumour. The iterative design and team implementation process was directed by the Extreme Programming (XP) methodology that allowed flexibility, constant assessment, and refinement of the system. The combination of sophisticated imaging tools and diversified group of patients made sure that the dataset included dynamic tumour properties which added strength to the suggested model.

As the experimental findings have shown, the brain tumour classifier developed using the YOLOv8 architecture provided a reliable result in the training and validation stages. This model achieved a precision of 0.85, recall of 0.75 and mAP50 of 0.80, which means that it has great detection and classification potential of brain tumours in MRI images. Though the mAP5095 value of 0.34 indicated the diminished robustness at high values of the IoU, the overall results suggest that yogaLO v8 can be used to analyse medical images, provided that it is complemented with proper preprocessing and feature enhancement, and transfer learning strategies. The integrated software system further validated the model's effectiveness by successfully performing real-time tumor detection, segmentation, and labeling on unseen clinical data.

In conclusion, the proposed system demonstrates the practical applicability of deep transfer learning for automated brain tumor diagnosis, offering a reliable decision-support tool for medical practitioners. By unifying detection, classification, and segmentation into a single workflow, the system enhances diagnostic accuracy and supports early intervention, which is critical for improving patient outcomes. Future work will focus on improving model robustness

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across higher IoU thresholds, incorporating multi-modal medical data, and extending the framework to other neuropathic disease classes to further enhance its clinical relevance and scalability.

## REFERENCES

Abdusalomov, A. B., Mukhiddinov, M., &Whangbo, T. K. (2023). Brain tumor detection based on deep learning approaches and Magnetic Resonance Imaging. *Cancers, 15*(16), Article 4172. https://doi.org/10.3390/cancers15164172

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

Bernetti, A., Agostini, F., De Sire, A., Mangone, M., Tognolo, L., Di Cesare, A., Ruiu, P., Paolucci, T., Invernizzi, M., & Paoloni, M. (2021). Neuropathic pain and rehabilitation: A systematic review of international guidelines. *Diagnostics, 11*(1), Article 74. https://doi.org/10.3390/diagnostics11010074

Ghosh, S., Biswas, S., & De, J. (2020). Automatic brain tumor detection and classification on MRI images using machine learning techniques [Project report]. National Institute of Technology, Durgapur, India.

Lam, C. M., Sanderson, M., Vu, D. T., Sayed, D., Latif, U., Chadwick, A. L., Staats, P., York, A., Smith, G., & Velagapudi, V. (2024). Musculoskeletal and neuropathic pain in COVID-19. *Diagnostics, 14*(3), Article 332. https://doi.org/10.3390/diagnostics14030332

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

Muhammad Imran Sharif, Muhammad Attique Khan, Musaed Alhussein, Khursheed Aurangzeb, & Mudassar Raza. (2022). A decision support system for multimodal brain tumor classification using deep learning. *Complex & Intelligent Systems, 8*(4), 3007–3020. https://doi.org/10.1007/s40747-021-00321-0

Thakkar, P., Greenwald, B. D., & Patel, P. (2020). Rehabilitation of adult patients with primary brain tumors: A narrative review. *Brain Sciences, 10*(8), Article 492. https://doi.org/10.3390/brainsci10080492

Tiwari, P., Pant, B., Elarabawy, M. M., Abd-Elnaby, M., Mohd, N., Dhiman, G., & Sharma, S. (2022). CNN based multiclass brain tumor detection using medical imaging. *Computational Intelligence and Neuroscience, 2022*, Article 1830010. https://doi.org/10.1155/2022/1830010

World Health Organization. (2020). *Nigeria*. https://gco.iarc.fr/today/data/factsheets/populations/566-nigeria-fact-sheets.pdf