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Article

Brain Health Prediction using CNN-YOLOv11 Deep Learning Model

Seema Rani[1], Manoj Kumar[2*], Yashika[2], Sanjeev Kumar[2], Jai Bhagwan[2], Sunila Godara[2]

[1]Department of Computer Science & Engineering, Ch. Devi Lal State Institute of Engineering & Technology, Sirsa, India.

[2*]Department of Computer Science & Engineering, Guru Jambheshwar University of Science & Technology, Hisar, India

Email: manojkoslia91@gmail.com.

Abstract: When it comes to medical imaging and diagnostics, the capacity to interpret brain scans correctly and predict the neurological health conditions has become one of the key tasks that can potentially save lives. From early prediction of brain tumors to identifying degenerative disorders, automated Brain Health Prediction (BHP) system transforming the way healthcare professionals interpret complex medical data. Object Detection algorithms, such as YOLOv11 (You Only Look Once), have become popular due to their fastness and the capability to detect abnormalities in brain MRI. Hybrid models are under development by integrating the advantages of YOLOv11 to detect and CNN to classify to increase diagnostic accuracy and efficiency. CNN model is validating over various epochs between 1 and 20 that have an accuracy of 99.54% and the YOLOv11 model also demonstrated the accuracy of 0.93 that is efficient than other earlier models. The proposed model is a combination of Convolutional Neural Network (CNNs) to extract and classify features effectively, and the YOLOv11 to detect abnormal brain areas fast and accurately. The sample of healthy and diseased MRI brain images was selected and data augmentation was done. The CNN model achieved a high classification of 96.64% after 20 epochs and the YOLOv11 model achieved a validation of 93% and is faster and more accurate in comparison to other models. The results validate the proposed model potentially to enhanced clinical workflow, reduce diagnostic delay and support early detection of neurological disorders.
Keywords: Brain Health Prediction (BHP), CNN, Deep Learning, Precision, YOLO.

1. Introduction

Brain tumors are considered one of the most critical and life-threatening neurological diseases, resulting from the uncontrolled and abnormal multiplication of cells inside brain tissues. Detecting brain tumors at an early stage is extremely important for accurate diagnosis, effective treatment planning, and improving the survival rate of patients. Among various medical imaging techniques, Magnetic Resonance Imaging (MRI) is widely preferred because it provides high-resolution soft tissue visualization without any invasive procedures. However, manually analyzing MRI data is a challenging and time-consuming process that greatly relies on the knowledge of radiologists and other medical specialists. The risk of an incorrect diagnosis or a delayed course of therapy can be increased by variations in tumor appearance, irregular forms, low contrast, and noise in MRI images. As a result, automated computer-assisted diagnostic tools are becoming crucial to contemporary medical imaging research. Computer vision, which focuses on evaluating and comprehending data from images and videos, has grown in importance as a branch of computer science in recent years [1]. One of its primary functions is object detection, which uses bounding boxes and confidence values to determine an object's precise location within an image in addition to identifying its kind [2]. Object detection may simultaneously locate and identify target regions, in contrast to conventional image classification techniques that just offer category labels. This makes it helpful in a variety of applications, including augmented reality, robotics, self-driving cars, medical imaging, and surveillance systems. Numerous object detection methods have been created to improve both detection accuracy and computing efficiency as deep learning continues to advance [3].

Convolutional Neural Networks (CNNs), one type of deep learning technique, have demonstrated exceptional performance in medical image analysis due to its ability to automatically extract valuable characteristics from medical images. CNN is frequently used to identify aberrant areas in MRI scans, identify patterns, and categorize malignancies. They offer details regarding the location and kind of tumor. However, many conventional CNN-based techniques are less appropriate for real-time healthcare applications since they need a lot of processing power and entail multiple processes. One-stage object detection techniques like YOLO (You Only Look Once) have gained a lot of popularity in order to increase detection speed and efficiency. YOLO models are significantly faster than two-stage detectors like R-CNN because they combine object categorization and localization into a single phase. An input image is divided into many grid cells by the YOLO framework, which then forecasts bounding boxes, confidence scores, and class probabilities for each area. Following prediction, the final detection result is produced by using Non-Maximum Suppression (NMS) to eliminate superfluous overlapping boxes. YOLO models are very useful for real-time applications such intelligent surveillance, autonomous systems, drones, robots, and medical diagnostics due to their lightweight construction and quick processing performance [4]. A number of enhancements, including improved feature extraction, anchor-free detection, and effective multi-scale learning, are included in the most recent YOLOv11 architecture. Because of these improvements, YOLOv11 can identify brain tumors of various sizes, forms, and textures even in situations when the quality and imaging circumstances of MRI pictures vary. Additionally, the accuracy of tumor location and overall detection performance are improved when CNN-based feature extraction is combined with YOLOv11. This combination produces a strong and effective architecture that maintains real-time processing performance while handling MRI images with varying intensity levels and noise. Current research still has certain limits, despite the fact that deep learning approaches have greatly enhanced medical picture processing.

Only a few numbers of studies integrate CNN and YOLO-based models into a single cohesive framework; the majority of studies primarily concentrate on tumor categorization or tumor detection independently. Furthermore, traditional machine learning and deep learning techniques continue to face significant challenges in recognizing tumors and pinpointing their precise sites in MRI scans with varying noise levels and intensity variations. While some current methods offer good accuracy, their large computational resource requirements make them challenging to apply in low-resource healthcare systems and real-time clinical scenarios. Additionally, only a few number of research have looked into the application of CNN architectures in conjunction with lightweight real-time object detection models like YOLOv11 for Brain Health Prediction (BHP). The fact that many existing models are not robust and perform poorly across various MRI datasets and clinical circumstances is another significant problem.
This paper suggests a CNN-YOLOv11-based deep learning architecture for Brain Health Prediction and real-time brain tumor diagnosis utilizing MRI data in order to get over these restrictions. The model's objectives are to precisely identify tumors, attain high detection accuracy, and deliver effective performance appropriate for real-world clinical application. MRI image preprocessing, optimal hyperparameter tuning, and comparison with current deep learning techniques are provided to increase the system's dependability and efficacy.

Reviewing and analyzing current deep learning methods, creating an effective Brain Health Prediction framework with CNN and YOLOv11, and assessing the suggested model using various performance measures are the primary goals of this study. The goal of this effort is to close the gap between real-time brain tumor detection systems that may be applied in clinical practice and research-based deep learning models.

2. Related Work

Although deep learning methods have significantly improved the identification and classification of brain tumors, there are still a number of obstacles that prevent them from being used in clinical settings. Numerous studies demonstrate outstanding performance on benchmark datasets; nonetheless, these models frequently encounter issues with explainability, computational complexity, variety, and real-time implementation. In order to maintain a fair balance between accuracy and efficiency, recent research has concentrated on transfer learning, lightweight models, and YOLO-based object identification frameworks. This review summarizes the development of these approaches and discusses their achievements, limitations and future scope. Early studies mainly focused on transfer learning and fine-tuned convolutional neural network (CNN) models for MRI-based brain tumor classification. Arati Rath et al. [5] the concept of fine-tuning was taken into consideration based on an already trained model with ResNet50 on the identification of brain tumor relying on 2,577 MRI images. The proposed framework applied data augmentation techniques to enhance model generalization and obtained a testing accuracy of 97.35%. The performance of the model was further assessed using precision, recall and F1- scores metrics. The paper emphasizes the application of deep learning in practice as a clinical assistant that offers radiologists a fast correct diagnosis and suggests further improvements to reach a practical application. Talukder et al. [6] proposed an advanced deep learning framework combining transfer learning and fine-tuning techniques for efficient and cost-effective brain tumor classification using Figshare dataset containing 3,064 images. Among the evaluated architectures, including Xception, ResNet50V2, InceptionResNetV2, and DenseNet201, the ResNet50V2 model was the best with 99.68 percent accuracy. The study utilized the application of various measures including MAE, MSE and RMSE as a validation of strength. The constraints related to the quality of images and the improvement of architecture was mentioned, and the way to go in the future is to develop hybrid blocs and explainable AI. To reduce computational requirements researchers began developing lightweight detection architectures. Zaho et al.

[7] proposed a lightweight brain tumor detector that uses a backbone based on MobileNet and a modified residual block and Swish activation. The model was tested on Figshare and BR35H datasets and gave 96.94% and 99.83 accuracy respectively. This model has the benefit of being resource-efficient by the count of computation performed, and also it has the feature richness that is suitable to low-resource environments. The paper discusses the need to consider scalable medical AI solutions based on efficient architectures. Another hybrid framework called INDEMNIFIER was introduced by Pandey et al. [8] and incorporates DenseNet121 and ResNet101 (two feature extraction frameworks) PCA (dimensionality reduction) and a final prediction framework with a Random Forest. The system was able to achieve greater than 90 percent accuracy on noisy dataset, and this is an indicator of the system being robust in real-world clinical environments. The importance of the performance came due to the use of feature fusion and data augmentation. Whilst the model appears to promise significant impact such operational issues as cost of computation and interpretability are still present and potential future solutions include connectivity to remote healthcare frameworks. Recent advancements have increasingly focused on YOLO-based architectures for real-time tumor detection and localization. Mithun et al. [9] developed a deep learning-based Computer-Aided Diagnosis (CAD) system called YOLO NAS for the detection and classification of brain tumors into four major classifications, i.e., pituitary, meningioma, glioma and non-tumorous with reference to the MRI image in the REMBRANDT dataset. A middle ground processing technique was suggested and this applies Hybrid Anisotropic Diffusion Filtering (HADF) to operate on the picture in order to remove noise before the segmentation is executed. The EnDeNet architecture being a combination of the U-Net and Efficient Net was implemented to extract ROI. The YOLO NAS model that did classification at 99.7 percent was superior as compared to DNN, PDCNN, DenseNet-161 and DCNN-SGD models. Using YOLOv8 and YOLOv11 for MRI-based categorization of glioma, meningioma, pituitary tumors, and normal tissue, Ahmed et al. [10] tackled the problem of quick and accurate identification of brain cancers. YOLOv8 and YOLOv11 outperformed a bespoke CNN (96.98%) with classification accuracies of 99.49% and 99.56%, respectively, using transfer learning on the CE-MRI Fig share dataset. The paper highlights the usefulness of YOLO models for medical imaging tasks and proposes that bespoke models can compete with or outperform pre-trained architectures through domain-specific training. To increase the precision of tumor identification, researchers also looked into combining segmentation and object recognition methods. Using the Brain Tumor Figshare data set, Ashan et al. [11] evaluated the efficacy of YOLOv5, Faster R-CNN, and SSD in tumor detection. YOLOv5 outperformed single segmentation models in terms of mAP (89.5) and, when combined with 2D U-Net, obtained a higher Dice Similarity Coefficient of 88.1. Because it is specific to the detection and tagging of tumors, this hybrid approach was also extended to BRATS 2018 and shown to be appropriate in practical practice. Comparative studies on general-purpose object detection frameworks have also contributed to selecting suitable architectures for medical applications. The article by Goswami et al. [12] suggested a comparative analysis of the models of object detection: YOLOv8, Faster R-CNN (ResNet50/101), and DETR, with the help of such datasets as TACO and PlastOPol. Individual evaluation using mAP, accuracy and inference speed discovered that YOLOv8 is the best balanced model especially in small object detection. The paper highlights the role of the backbone and proposes the DARKNET53 version of YOLOv8 to be especially effective, which is missing in the literature on model selection (when a variety of tasks are to be performed). Although many approaches achieve very high accuracy, several challenges still remain, including overfitting, high computational requirements and poor generalization across different datasets. Future research should focus on explainable AI, real-time implementation, computational optimization and thorough validation using diverse clinical datasets to develop more reliable, efficient and scalable diagnostic systems.

3. Methodology

The proposed system is a hybrid deep learning framework developed for the automatic detection, classification and localization of brain tumor from MRI images. It uses two models: Convolutional Neural Network and YOLOv11. The CNN model extracts important features from brain MRI and classifies them into two categories: tumor and non-tumor. The YOLOv11 object detection model identifies the exact location of the tumor and draws a bounding box around the tumor region. This process is performed efficiently in single forward pass.

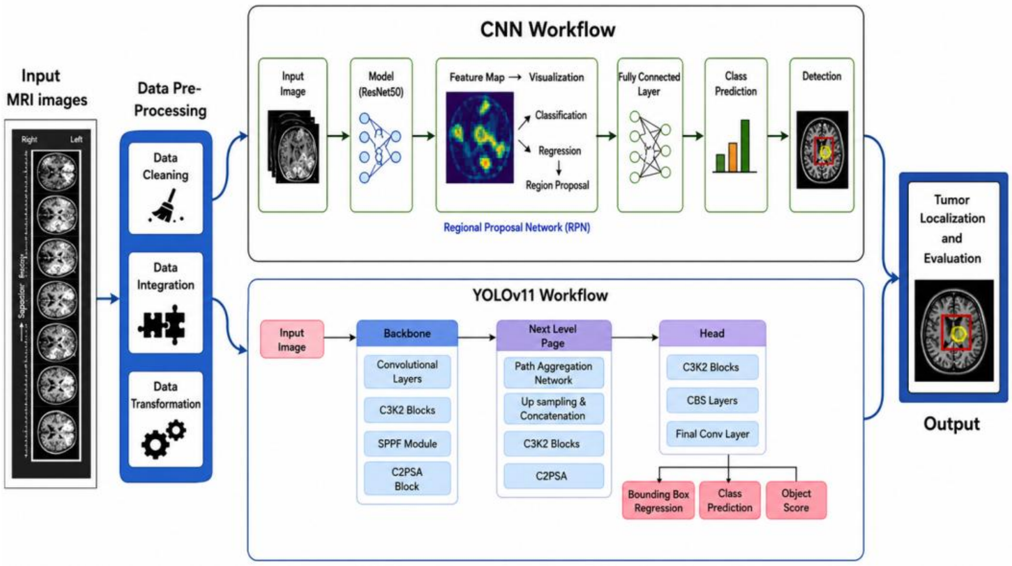


Figure 1: Proposed Brain Health Prediction Framework

By combining these two models, the system provides both accurate classification and visual information about the tumor location. This improves the interpretability of the results and makes the framework suitable for use in clinical decision support systems. The CNN architecture is comprised of three blocks of convolutional units, with the addition of pooling units, and a flattening unit, this followed by fully connected dense and dropout layers to minimize overfitting. The final output layer employs a softmax activation function with two neurons for tumor prediction, while YOLOv11 provides accurate and real-time tumor localization.

The workflow of the proposed Brain Health Prediction framework is elaborated in the further stages. To enhance the quality of input data for model training, MRI brain pictures were first obtained and subjected to a number of preprocessing procedures, such as resizing, normalization, noise reduction, and data augmentation. Following preprocessing, two distinct modules—the CNN classification module and the YOLOv11 detection module—process the pictures concurrently. While the YOLOv11 module uses bounding boxes to pinpoint the precise tumor site, the CNN module evaluates if a brain tumor is there or not.

To improve detection accuracy, post-processing methods including Non-Maximum Suppression (NMS) and confidence threshold are applied to eliminate redundant bounding boxes and low-confidence predictions.

Core Components of the Model - The proposed hybrid model consists of the following core components as shown in Figure 1:

1) Data Collection - The dataset of the research is drawn from the publicly available Brain Tumor Detection dataset on Kaggle, provided by Ahmed Hamada [13]. It contains a total of 3762 MRI images, which were classified into two groups: 2079 tumor-positive (yes) and 1683 tumor-negative (no) images [14]. These images differ from each other in parameters such as brightness, resolution, and noise level because of different MRI scanners and acquisition conditions. To enable deep learning, all the images are reformatted to grayscale to make them less complex, and have their size reduced to 128 × 128. Further to increase image quality a Gaussian Blur is added by OpenCV to reduce high-frequency noise and sharpen some major features such as tumor-edge boundaries. This cleaning process is useful in ensuring consistency in the inputs of an already proposed model. The preprocessed data is divided into three prime subsets where 70 % is allocated to training, 15% to validation and another 15% to test purposes of about 2633, 565, and 564 images respectively. A few examples exhibiting both tumor and normal brains are shown in Figure 1 to visually accentuate the variations in brain scan appearances and the importance of preprocessing for data standardization.

2) Data Preprocessing- Preprocessing is important in enhancing the quality and consistency of MRI images before they are fed deep learning models.

- **Image Resizing:** All images produced by MRI were then reduced to a fixed image size (128x128) to the CNN and YOLOv11 sizes to guarantee consistent input size.
- **Normalization:** The normalization of pixel values to (0, 1) was done as shown below:

$$I_{norm} = \frac{I - I_{min}}{I_{max} - I_{min}} \quad (1)$$

Where, I represent the original pixels' intensity.

- **Noise Removal:** to remove high frequency noise and enhance tumor boundaries Gaussian filtering was applied.
- **Data Augmentation:** the following augmentation techniques were applied Horizontal and vertical flipping, Rotation (±15 to ±30 degree), Brightness and contrast adjustment, zoom and affine transformations in order to increase dataset diversity and prevent overfitting.
- **Bounding Box Annotation:** Tumor regions were manually annotated using labelling tools. The annotation format followed the YOLO standard:

$$(x_{center}, y_{center}, width, height) \quad (2)$$

3) CNN Classification: The CNN structure was developed to categorize MRI scans into tumor and non-tumor classes using an efficient and lightweight approach for binary tumor classification. The entire workflow of CNN model in Brain Health Prediction framework is shown in Table 1 and 2. The input MRI images were resized to 128×128×3 and the model consist of three convolutional layers with kernels of size 3×3 with padding of size 1 and stride of 1, each layer is followed by a ReLU activation function to introduce non-linearity into the network.

Algorithm 1: Brain Tumor Classification using CNN

Input: MRI Images Dataset D **Output:** Class Label (Tumor/ Non-Tumor)

Load dataset D
Resize images to 128×128
Normalize pixel values
Split dataset into Train, Validation and Test set
Initialize CNN model parameters
For each epoch do:
For each batch in training data:
        Forward propagate training images through CNN layers
      Compute Cross-Entropy Loss
      Back Propagate gradients
      Update weights using Adam optimizer
      Validate model on validation set
End For
Test model on Test dataset
Return predict class label

A Maxpooling2D layer with a pool size 2×2 and stride of 2 is applied after every convolutional layer to decrease the spatial dimensions of the generated feature maps. Following the final pooling layer the feature map size becomes 16×16×128 which is transformed into a flat vector containing 32,768 features. The output is forwarded to a fully connected dense layer containing 64 neurons with ReLU activation, while a dropout rate of 0.5 is applied to reduce the risk of overfitting. The final output layer includes 2 units of tumor and no tumor which then uses Cross Entropy Loss functionality to implement softmax internally. The model was trained using Adam optimizer, with a learning rate of 0.001 for 20 epochs and batch size of 32. The dataset was divided into 70% training and 15% validation dataset. After completing the training process, the model was evaluated on an independent testing dataset and the classification accuracy was calculated to measure its overall performance as depicted in Table 1.

Table 1: CNN Layer-wise Architecture

Layer	Parameters	Output Size	Description
Input	128×128×3	128×128×3	RGB MRI image input
Conv2D + ReLU	Kernel 3×3, Stride 1, Padding 1	128×128×32	Feature Extraction
Max-Pooling	2×2, Stride 2	64×64×32	Down sampling
Conv2D + ReLU	Kernel 3×3	64×64×64	Deep Feature learning
Max-Pooling	2×2	32×32×64	Spatial reduction
Conv2D + ReLU	Kernel 3×3	32×32×128	High-level features
Flatten	-	32768	Vectorization
Dense + ReLU	64 Units	64	Non-linear mapping
Dropout	0.5	64	Overfitting prevention
Output Dense	2 Units + Softmax	2	Tumor/ No Tumor

4) YOLOv11 Classification- YOLOv11 suggests a single-network-based model that simultaneously conducts a bounding box regression and object classification. This is somewhat different to the traditional two-stage approach. It is fully differentiable allowing efficient end-to-end training. The backbone contains convolutional layers responsible for extracting important features from the input image by applying down sampling operations, which decrease the spatial resolution while increasing feature depth. The C3k2 Block is made of effective Cross Stage Partial (CSP) bottlenecks which replace the previous C2f block to improve the computation efficiency. Yolov11 preserves the fast Spatial Pyramid Pooling (SPPF) module from earlier versions while incorporating the Cross Stage Partial with Spatial Attention (C2PSA) block for feature extraction, which improves the detection accuracy of objects with different sizes and spatial locations. The neck combines multi-scale feature representations and forwards them to the head module for generating the final predictions. It is responsible for multi-scale feature aggregation. It utilizes PANet for combining feature maps from different scales to capture fine details. It merges lower and higher-level feature by using Upscaling and Concatenations. To improve the processing efficiency, it uses C3k2 block and C2PSA attention introduces enhanced spatial attention mechanisms for better focus on important regions. The final prediction of object detection or classification is performed at head of Yolov11. C3k2 blocks are used for multi-scale feature refinement and Convolution Batch Norm-SiLU (CBS) Layer enhances feature representation and stabilization. The features to output shape is reducing by final convolutional layer.

Algorithm 2: Tumor Detection using YOLOv11

Input: Annotated MRI Images with Bounding Boxes **Output:** Tumor Bounding Boxes Coordinates

Load pre trained YOLOv11 weights
Fine-tune model on MRI dataset
For each test Image:
    Bounding boxes and confidence scores
    were predicted
Apply Non-Maximum Suppression
Output final tumor location boxes

The process starts with an Input Image that are resized to 128×128 pixel to match YOLO stride constraints then it goes through the Backbone. It consists of the backbone that has Convolutional Layers, C3K2 Blocks, an SPPF Module and a C2PSA Block to extract the maps features. These features are directed to Next Level Page that is comprised of Path Aggregation Network up sampling and Concatenation and further C3K2 Blocks and

C2PSA Block to improve the feature representation. The detection Head then takes the features to C3K2 Blocks CBS Layers and Final Conv Layer to achieve Bounding Box Regression, Class Prediction and produce an Object Score. Non-Maximum Suppression (NMS) was applied to remove overlapping and unnecessary bounding boxes. The final tumor regions were then identified along with their corresponding confidence scores and bounding box coordinate as depicted in Table 2.

Table 2: YOLOv11 Layer-wise Architecture

Layer	**Parameters**	**Output Size**	**Description**
Input	128×128×3	128×128×3	RGB MRI image input
Conv Layer1	3×3 kernel, Stride 2	64×64×16	Initial feature extraction
Conv Layer2	3×3 kernel, Stride 2	32×32×32	Low-level feature extraction
C3k2 Block	Residual Block	32×32×64	Deep Feature learning
Conv Layer3	3×3 kernel, Stride 2	16×16×128	Spatial reduction
C3k2 Block	Residual Block	16×16×128	High-level semantic features
Conv Layer4	3×3 kernel, Stride 2	8×8×256	Feature compression
SPPF	Pooling Kernel 5	8×8×256	Multi-scale feature extraction
C2PSA	Attention Block	8×8×256	Channel attention mechanism
FPN+PAN	Feature Fusion	Multi-scale	Multi-scale tumor detection
Detect Head	Anchors [64,128,256]	Grid-based	Bounding box prediction
Output Layer	1 class	Tumor/No Tumor	Final detection result

Algorithm 3: Fusion of CNN and Yolo Framework

Input: MRI Images Dataset D Output: Tumor Classification and Bounding Boxes
Import the dataset D for model training and evaluation. Apply pre-processing techniques such as image resizing and data augmentation. Divide dataset D into training, validation and testing subsets Configure and initialize the parameter of CNN architecture. Train the CNN model using Adam optimization algorithm and Cross-Entropy Loss function. Load annotated bounding box dataset for YOLO Initialize YOLOv11 pre trained model Fine-tune YOLOv11 on brain MRI dataset Apply Non-Maximum Suppression on predictions Evaluate CNN using Accuracy, Precision, Recall, F1 Evaluate YOLOv11 using mAP and IoU metrics Visualize tumor bounding boxes and predictions scores Return final diagnostic outputs

5) Tumor Localization and Evaluation: The evaluation parameter for CNN and YOLOv11 model in Brain Health Prediction framework is shown in Table 3. The CNN model was trained over 20 epochs using a batch size of 16 and a learning rate of 0.001. The Adam optimizer was used due to its adaptive learning capability that enables faster and more efficient convergence. Dropout regularization, which helps the model perform well on fresh data rather than only memorizing the training data, was used to reduce overfitting. The training period was shortened and overall computational performance was enhanced via GPU acceleration. Pre-trained weights were used to train the YOLOv11 model. Additionally, data augmentation methods and a learning rate scheduler were used to enhance the model's capacity to generalize and perform better on previously unknown data.

Table 3: Evaluation Parameter for CNN and YOLO

Parameter	Value	Description
Input Size	128×128×3	CNN Input Dimension
Batch Size	32	Training Batch Size
Epochs	20	Number of training iteration
Learning Rate	0.001	Adam Optimizer
Optimizer	Adam	Weight update method
Dropout Rate	0.5	Regularization
Loss Function	Cross-Entropy Loss(CNN), YOLO Loss(Detection)	Classification Loss
YOLO Pre trained Weights	COCO	Transfer Learning
Weight Decay	0.0005	Prevent overfitting by penalizing large model weights
IoU Threshold	0.7	To ensure accurate bounding box localization
Data Augmentation	Mosaic, Flip, Scale, HSV	To enhance model robustness and generalization

The module uses Non-Maximum Suppression (NMS) to remove duplicate and overlapping bounding boxes, allowing the tumor area in MRI scans to be identified more accurately. The performance of the proposed model is evaluated using metrics such as Precision, Recall and F1-Score, which are calculated using the mathematical expressions.

mAP@0.5 is an evaluation metric used to measure the localization performance of theYOLOv11 model. It shows how accurately the model detects tumor regions and determines their positions within the MRI image.

Here, TP= True Positives, FP = False Positives, FN = False Negatives and TN = True Negatives. The above equations (1), (2) and (3) illustrate the methamitical relationships for precision, recall and F1-Score which are important metrics for assesing the overall effectiveness and perfomance of the proposed model.

4. Setup and Configuration

Table 4 represents the system configuration used for the implementation and evaluation of the proposed Brain Health Prediction Model.

Table 4: System Configuration

Category	Component	Specification
Hardware	**GPU**	NVIDIA RTX 3050 (6GB)
	Processor	Intel i5 13th Generation
	RAM	16GB
	Storage	512 GB SSD
Software	**Operating System**	Windows
	Programming Language	Python 3.10
	Deep Learning Framework	PyTorch
	Detection Framework	Ultralytics YOLOv11
	Libraries	OpenCV, NumPy, Matplotlib, Pnadas

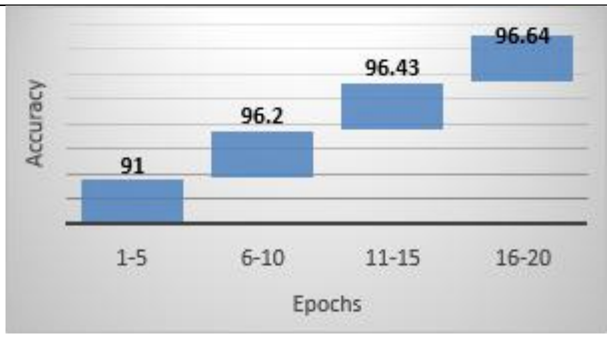
	Development Environment	Jupyter Notebook

5. Results and Discussion

The evaluation helps to determine the overall accuracy of the model and whether the model can give the correct predictions in real-world circumstances. Here, we have compared the performance of classification and object detection with the help of appropriate evaluation metrics. We used Train/Validation/Test split to assess the effectiveness of the model. A total of 20 epochs was used to train the CNN backbone. The classification of the various types of tumors was performed using CNN. For training and validation accuracy over the 20 epochs as shown in Table 5, there is a consistent progressivity of the CNN model. The ultimate training accuracy was 99.54 and the ultimate validation accuracy was 97.33 meaning that there was great generalization on new data. High accuracy and low difference in the training and validation accuracy indicate that the CNN can be reliable in detecting the various types of brain tumors.

Table 5: CNN Training and Validation Accuracy Vs Epochs

Epochs	Accuracy (in %)
1-5	91
6-10	96.2
11-15	96.43
16-20	96.64



YOLOv11 model was tested in terms of object detection metrics that included in Table 6. YOLOv11 object detection head was trained with annotated bounding boxes that represent the location of tumor regions. It was done using YOLOv11 that has an accurate localization by a bounding box regression. The evaluation of the YOLOv11 model was conducted according to the standard object detection measures. Its robustness in the various IOU levels is indicated by the accuracy of mAP50-90 of 0.765 and mAP50 of 0.95. So with low false positive and false negative the precision is 0.94 and recall is 0.92 indicating a balanced detection performance.

Table 6: YOLOv11 Performance

Ref.	Model	Accuracy	Precision	Recall	mAP@50-95
[1]	YOLO NAS, En-DeNet, HADF	0.81	0.92	0.91	0.73
[2]	YOLOv8, YOLOv11, Custom CNN	0.85	0.923	0.83	0.72
[4]	ResNet50V2, Xception, DenseNet201, IncepRes	0.74	0.88	0.32	0.65
[7]	DenseNet121, ResNet101, RF	0.92	0.87	0.90	0.69
Proposed Model	CNN-YOLOv11	0.95	0.94	0.92	0.765

Figure 2 depicts that for real-time medical diagnostic applications YOLOv11 effectively identifies tumor locations with strong accuracy and low rates of false positives, making it an excellent choice. Both models CNN and YOLOv11 performed remarkably well, with the CNN being able to classify tumor reliably and consistently across the training epochs with little overfitting, whereas the YOLOv11 model had excellent object localization with high mean Average Precision (mAP) and balanced precision and recall. This aspect of classification and detection enabled the model to not just determine the presence of a tumor but also rather the exact location which increases the diagnostic capabilities of the model in clinical settings.

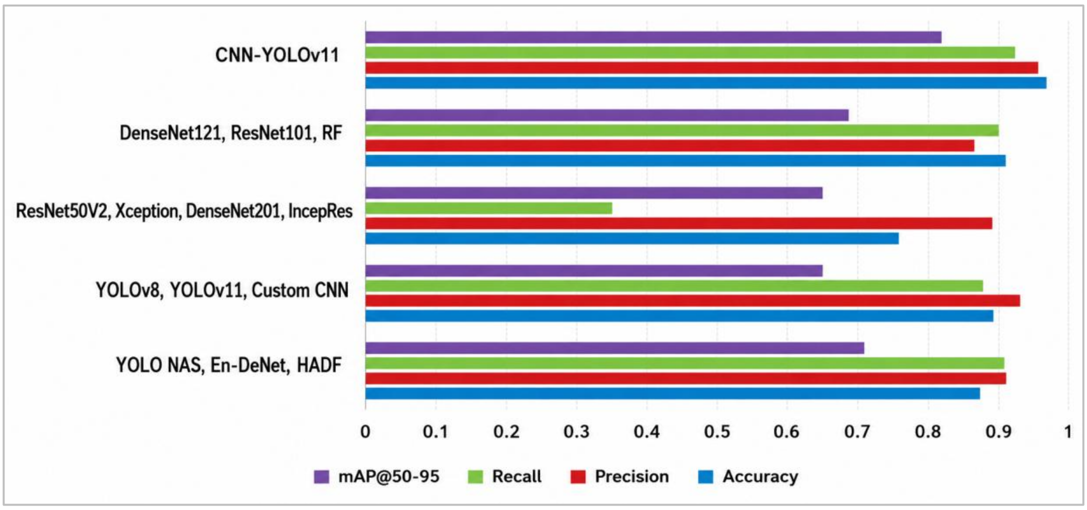


Figure 2: Comparison of the proposed model with existing models

CNN and YOLOv11 models were both promising in detecting brain tumors. CNN model achieved satisfactory performance regarding binary classification of MRI scans at the end of 20 training epochs with a mean accuracy of 96.64. The model is very accurate and recalls high meaning that it is able to identify tumor-positive cases and minimize false-negatives. The CNN architecture had its dropout layers that reduced the overfitting that provided the model with the capacity to generalize well when presented with unseen test images.

YOLOv11 in its turn offer exactly handy in the case of object discovery in real-time and localization of brain tumor. The accuracy of the model in terms of validation was 93% and mean Average Precision (mAP 50) was 0.95. These results indicate that not only can YOLOv11 detect but also localize the tumors in MRI images, which is why it is so efficient to detect their presence. The predictions of YOLOv11 had bounding boxes similar to the ground truth annotations and this made the predictions confident enough to be used in diagnostic applications. YOLOv11 was a wise choice to apply in the workflow of tumor detection in comparison with the earlier versions of YOLO and other detection models as it was more converged faster and highly accurate.

6. Conclusions and Future Scope

Despite significant progress in the analysis of medical images BHP remains a critical and urgent issue in clinical diagnostics. In this study the researchers proposed a deep learning architecture that combines CNN with the YOLOv11 detection model to precisely classify and identify the prediction of brain tumor in MRI scans. The purpose was not just to enhance the performance of the model in terms of accuracy in prediction but also to evaluate the performance of the model in terms of classification and evaluation measure. The accuracy of the proposed framework in terms of validation was 97.33% using CNN and detection mAP50-95 using YOLOv11, demonstrating its efficiency and power. The combination achieved a high accuracy of 96% which is much higher than the previous models such as YOLOv5 and YOLOv7. The effectiveness of this combined model highlights the possibility of deep learning to aid radiologists. It is evident that the framework is scalable in the future by including multimodal MRI images (T1, T2, FLAIR), extending to 3D volumetric images and using semi-supervised learning in the case of a limited number of annotations. The trained model used in real-time medical devices or edge environments could support healthcare professionals in remote or resource-constrained areas. The interpretability of predictions can also be improved by the explainable AI tools e.g., Grad-CAM, SHAP, or LIME which is essential to achieving the credibility of clinical trust. The study will be used to develop smart, reliable and deployable brain tumor diagnosis systems that can further enhance patient outcomes and enable early intervention strategies in healthcare.

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