Deep Learning: A Revolutionizing Approach To Brain Tumor Classification Using MRI

Vikram Verma[1, 2], Alankrita Aggarwal[3]

[1]*Department of CSE, Chandigarh University, (Gharuan), Mohali, India*
[2]*CSE department, Panipat Institute of Engineering & Technology, Haryana, India*
[3]*Professor, CSE Department, AIT, Chandigarh University, (Gharuan), Mohali, India*

***Corresponding author(s).** Vikram Verma and Alankrita Aggarwal*
**E-mail(s): mail4vikram@gmail.com; alankrita.agg@gmail.com*

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Abstract
Brain cancer, caused by tumors formed through the irregular and unchecked proliferation of brain cells, poses significant risks, including permanent brain damage and even death if left unmanaged. The number of individuals impacted by brain tumors (BT) is rising worldwide. Positional accuracy and tumor size play a key role in traditional treatments. Thus, creating an automated and meticulous approach to deliver critical information to healthcare professionals is of utmost importance. The integration of various imaging modalities with machine learning (ML) along with its various subsets like deep learning (DL) has enhanced physicians' ability to identify tumor types with increased precision and reduced time. This paper aims to provide insights into recently developed systems that utilize these techniques to analyse medical imaging for BT diagnosis. Lastly, this paper discusses the major challenges faced by DL algorithms in BT classification and potential advancements in this field. Lastly the paper discusses the use of YOLOv8 and compares its results with the customized CNN (CCNN) BT classification technique. The accuracies obtained were 98.94% and 96.88% respectively.

Abbreviations

BT	Brain tumor	TCIA	The Cancer Imaging Archive
BTC	Brain tumor classification	FCM	Fuzzy C-means
ML	Machine Learning	GWT	Gabor Wavelet Transform
DM	Data Management	CM	Confusion Matrix
DL	Deep Learning	MRI	Magnetic Resonance Imaging
CCNN	Customized CNN	TL	Transfer Learning
CNN	Convolutional Neural Networks	YOLO	You Only Look Once

I. Introduction

The dynamic brain which is the hub of nervous system requires utmost protection both physically and any form of disease. The number of individuals impacted by BT is on the rise worldwide. The global incidence of brain tumors is steadily rising. The WHO reports around 300,000 new brain tumor cases yearly [1].
Medical imaging modalities contribute significantly to patient diagnosis and treatment in clinical settings [2]. As technology in medical science advances, the utilization of imaging techniques in medical radiation is on the rise [3]. MRIs are non-invasive imaging methods for medical diagnosis. [1,2]. The concept of MRI is based on detecting alterations in the rotational direction of protons within the water molecules of living tissues, utilizing advanced technological methods [3]. MRI are useful for visualizing soft tissues and non-bony structures without employing x-rays or radiation, making them ideal for diagnosing brain aneurysms and tumors. It is widely utilized because it has the ability to differentiate between the white and grey matter within the brain. [4,5]. Machine learning and DL, vital components of Artificial intelligence, have lately become widely popular in healthcare domain [1]. Diagnostic support systems for brain tumors using these approaches are being created [1,3,4,5]. Certain systems focus on single datasets, whereas others incorporate multiple datasets.
The article mainly focuses on the following research points:

- This work analyses recent advancements in brain tumor diagnosis systems employing ML and DL approaches. This review covers the most significant methods used for BT detection.
- The authentic source of data a researcher can work on.
- The discussion section highlights key challenges and potential future research areas.
- Finally, the paper also presents two methodologies used by authors for the classification of BT.

II. Literature Review

Brain Tumor Diagnosis with Machine Learning

The K-Nearest Neighbour (K-NN) algorithm, a core classification process, was used by Ramdlon et al. [4] for categorizing the BT. This research was designed to classify brain tumor types, including astrocytoma, glioblastoma, and oligodendroglioma, using data from TCIA. The team got a 89.50 % classification accuracy.
A team of Gurusamy et al. [5] described a Support vector machine method (SVM) for BT analysis, tumor detection, and extraction. For research the team used Cheng Figshare [6] data. Noise is removed using a comprehensive pre-processing. The team got an overall accuracy of 98.00%.
A team of Amin et al [7] used ML for BTC with Local Binary Pattern and GWT method to develop a system. Their dataset was BraTS The model had an accuracy of 97.00%.
Nilesh [9] and team used a classification model that combined Berkeley wavelet transformation (BWT) for segmenting BTs with SVM used as classifier. The research utilized two datasets: the DICOM dataset, which included 22 images, and the Brain Web data. The developed model demonstrated an accuracy of 96.51%, in distinguishing normal and diseased tissue.
Lalitha [10] and the team presented several noise elimination strategies. They combined balance-contrast enhancement technique (BCET) to increase the accuracy of BT classification. Fuzzy C-means (FCM) clustering was applied for MRI subdivision. The Brain Web data was utilised which provided simulated 3D MRI images. After applying filter, FCM and thresholding techniques were utilized, yielding an accuracy of 98.12% and sensitivity of 87.83% in detecting abnormalities.
A study conducted by Parveen et al. [11] introduced hybrid methods using SVMs and FCM for BT detection. The MRI used in this research were sourced from [12], and the dataset was classified in 02 classes: tumorous and non-tumorous. The researchers achieved result with an accuracy of 91.66%.
The study by Altaei et al. [13] developed an investigation scheme to classify BTs as normal or abnormal and further categorize them into benign or malignant. The system extracted features from MRI images using the SIFT descriptor. A Naive Bayes classifier was applied to discriminate between normal and abnormal BTs, and the J48 classifier was then used to catalogue abnormal BTs as either benign or malignant. The dataset was sourced from radiopedia.com, a site specializing in private-sector medical research. They got accuracy of 98.9%, and the J48 classifier attained a flawless 100% accuracy rate.
The work by Cheng et al. [14] showcased the classification accuracy of BTs by using CT scans as well as and CE-MRI. The CE-MRI was composed using Tianjing Medical University and Nanfang Hospital in Guangzhou, China. Classification of the BTs was performed using an SVM with a histogram intersection kernel. The researcher could get an accuracy of 91.28%.
A team of Alam et al. [15] offered a novel approach using K-means and FCM procedures for BT detection. The dataset compiled for the study was derived from various sources [17–19]. The system demonstrated an accuracy of 97.5%.

Brain Tumor Diagnosis with Deep Learning

DL involves analyzing data using multilayered algorithms. Multiple layers are used to process data, with each layer using information from the one before it to determine the result at the next layer.
For BT classification, Mohsen et al. [16] devised a deep neural network classifier. They used data from Harvard Medical School website. For extraction discrete wavelet transformation (DWT) was used. Further the model also used principal component analysis (PCA). The model reached an accuracy of 93.94% . Further the model had an F1-score of 96.3%.
Abiwinanda et al. [17] conducted a further study with CNN for BT classification. The study employed 3064 MRI from [6] dataset. The MRI were stored in MATLAB format (.mat file). The train data was 71% and the rest of 29% for validation. They achieved an accuracy of 84.19%.
A research team of Sunanda [18] used CNN for classifying BTs. The Figshare [6] dataset was used. The data was fragmented into 3 parts - 66.9% for training, 16.3% for testing, and 16.7% for validation. Gaussian filter removed the noise. The method achieved a test accuracy of 94.39%. Adam optimiser was used for for training. The model had an average precision of 93.33%. Further the model got 93.00 % recall.
In their investigation, Swati [19] and the team built a content-based MRI retrieval model using TL. The system was intended to classify BT using Cheng [6] data. Closed-form metric learning was used. Partitioning of dataset was done. 75% images for training and 25% for validation. The study used pretrained VGG19. They got in an overall accuracy of 96.13%.
The research by team of Deepak [20] achieved accuracy of 98.00%. Cheng dataset [6] was employed. The investigators used GoogleNet for BT classification.

Capsulenet-based technique was employed by Vimal [21] for BT classification. The work was carried on Cheng dataset [6] . It was segregated into 80.00% train and 20.00% test groups. The prototypical achieved accuracy of 92.60% [2].

The algorithm proposed by Narmada Balasooriya et al. [22] utilizes CNNs for tumor classification. The CNN model was built and trained using cross-validation. The research incorporated three open-source datasets. The first is TCIA. It contained MRI images from 100 patients, The University of Edinburgh's Image Bank repository served as the source for the second dataset while the third dataset came from MIRIAD, often used in Alzheimer's disease studies. Achieving F1-score of 99.46%, the model showcased remarkable performance.

Aaswad et al. [23] applied a five-layer CNN to detect BT from MRI images. The datasets used in their study [30–31] included a total of 1800 MRI. Among the total samples, 900 were identified as cancerous and 900 as non-cancerous. The authors recorded a training accuracy of 99.00% alongside a validation accuracy of 98.60%.

AlexNet model along with Region Proposal Network (RPN) was employed by Ezhilarasi et al. [24] in their research. For training RPN was used with faster R-CNN architecture. Sources included *www.sciencesource.com* and *www.radiologyassistant.nl* for MRI. This data formed the foundation for the study. It contained 50 MRI images, each with a size of 320 × 440 pixels. The model demonstrated an accuracy of 99%.

In their study on 16-layer CNN model, Hossam Sultan et al. [25] classified BT using publicly available datasets. They used two data sources. On TCIA data they achieved 98.7% accuracy. While on Cheng [6] data it yielded an accuracy of 96.13%.

VGG-16 was employed by Sajjad et al. [26] to classify BTs. , leveraging considerable data augmentation. Their research incorporated two datasets: A) the Radiopaedia dataset. This has got 121 MRI split into four grades. B) The Figshare dataset [6], containing 3064 contrast enhanced (T1c MRI) images. The model achieved 90.67% accuracy, and 99.4% specificity.

Pashaei and team [27] gave a classification system that relies on the CNN for feature extraction. The researchers further applied kernel Extreme Learning Machines for the purpose of classification. The adopted method gave an accuracy of 96.38%. In their work, the data used was taken from Cheng Figshare [6].

Hashemzehi et al. [28] built a hybrid model for BTC founded on CE-MRI figshare data [6]. CNN was integrated along with the neural autoregressive distribution estimation (NADE). They focused on feature extraction and automatic data distribution estimation. Leaning was done in three stages. The proposed BT classifier achieved 95% accuracy.

Rehman et al. [29] demonstrated TL classification system. AlexNet, GoogleNet, and VGG16 were used. The Figshare dataset [6], created by Cheng in 2017, was used for this research. The proposed system achieved accuracies of 97.39% for AlexNet, 98.04% for GoogleNet, and 98.69% for VGG-16.

Cinar et al. [30] used a hybrid CNN algorithm for BTC. For this research data was obtained from the Kaggle . The ResNet50 CNN prototypical served as the base, with its final five layers were eliminated and replaced by eight fresh layers. The algorithm attained an accuracy of 97.20%. In addition, the models AlexNet, ResNet50, DenseNet201, InceptionV3, and GoogleNet were evaluated, yielding an overall accuracy of 97.01%.

A DL multimodal classifier for BT classification was given by Khan et al. [31]. Feature extraction was performed by VGG16 and VGG19. The analysis was conducted with 03 BraTS datasets. Further for classification Extreme Learning Machine was used. This classifier gave an accuracy of 97.8% using the BraTS 2015 data, 96.9% on the BraTS 2017 and 92.5% on the BraTS 2018 data.

Region Proposal Network (RPN) was employed by Bhanothu et al. [32] recently. The framework used faster R-CNN, a DL technique. They used [6] dataset. Further VGG-16 acted as the foundational network to create the convolutional feature map for the tumor region in Faster R-CNN. The outcomes revealed an average recall of 77.60% across all classes.

Using TL and deep CNN, researchers Kang et al. [33] extracted deep features from MRI in their study. The team used three Kaggle datasets. The authors evaluated 13 pre-trained CNN frameworks to assess which method proved most effective for extracting features during the BT classification. DenseNet-169 attained the maximum accuracy, with a result of 93.72% in conjunction with SVM.

Table 1 includes various other related research works.

TABLE I. SUMMARY OF THE PROCEDURES USED IN BT DETECTION

Sr No	Year	Ref No.	Technique	Dataset	Images used	Accuracy %	Remark (Total Tumor classification classes)
1.	2024	[34]	Hybrid VGG16– ResNet-50	Kaggle	3264	99.98	3 (Meningioma, Glioma, Pituitary)
2.	2024	[35]	DeepCNN_WSSOA	Figshare	3064	99.29	Tumor or non-tumor
3.	2024	[36]	Yolov5 Yolov7	Figshare	3064	94.70 94.10	3 (Meningioma, Glioma, Pituitary)
4.	2023	[37]	CNN, Auto encoder	GitHub	3264	96.47, 95.63	3 (Glioma, Meningioma, Pituitary)
5.	2023	[38]	CNN, ResNet-50 , Inception-50, VGG 16	Kaggle	3264	93.30 81.10 80.00 71.60	3 (Meningioma, Glioma, Pituitary)
6.	2023	[39]	FastCNN	Figshare	3064	98.86	3 (Meningioma, Glioma, Pituitary)
7.	2023	[40]	Graph Neural Network	Kaggle	3264	95.01	3 (Meningioma, Glioma, Pituitary)
8.	2022	[41]	CNN and attention mechanism	Figshare	3064	98.61	3 (Glioma, Meningioma, Pituitary)
9.	2022	[42]	Hybrid Deep Neural Network	Private Hospital	1250	98.7	Tumor or non-tumor
10.	2022	[43]	Bayesian optimized CNN, VGG16, VGG 19, ResNet 50, DenseNet 201, InceptionV3	Figshare	3064	 98.70 97.08 96.43 89.29 94.81 92.83	3 (Meningioma, Glioma, Pituitary)
11.	2021	[44]	U-NET , CNN	BraTS 2015	274	96.36	1(Tumor – Glioma)
12.	2021	[45]	CNN	Figshare	3064	94.74	3 (Glioma, Meningioma, Pituitary)
13.	2020	[46]	AlexNet GoogleNet VGG-16 CNN	Figshare	3064	97.39 98.04 98.69	3 (Glioma, Meningioma, Pituitary)
14.	2020	[47]	3D CNN	BraTS 2018	284	96.49	1(Tumor – Glioma)
15.	2020	[48]	FAHS-SVM	Private	400	98.51	Tumor or Non tumor
16.	2019	[49]	CNN	Figshare 2017	700	98.51	3 (Meningioma, Glioma, Pituitary)
17.	2019	[50]	Fused feature adaptive firefly backpropagation neural network	BraTS 2015	81	99.84	Classify into benign and malignant cancer
18.	2019	[51]	CNN + GA	IXI dataset, REMBRANDT	600, 130	94.20, 90.9	3 (Meningioma, Glioma, Pituitary)
19.	2018	[52]	Statistical thresholding and Multiscale CNN	BRATs 2015	274	86.30	Tumor or non-tumor
20.	2018	[53]	Multiview DNN	BraTS 2017	146	88	Tumor or non-tumor

III. Discussions And Challenges

Discussions regarding the examined systems, encountered challenges, and envisioned future directions are presented in this section.

Our investigation focused on 47 brain tumor diagnostic systems, where 38 systems (86.36%) leveraged DL architectures, and 09 systems (19.14%) used machine learning techniques. Regarding the data sources, 13 systems (27.65%) worked with multiple datasets, and 34 systems (72.34%) relied on a single dataset.

A significant number of have used the Cheng Figshare [6] dataset, which contains data from 233 patients diagnosed with 03 types of BTs. This demonstrates the dataset's popularity and its well-organized nature, making it a go-to resource for BTC tasks. The other popular dataset is BraTS.

Challenges and Future Trends.

There are abundant challenges when applying DL for brain cancer detection from images. While large datasets, especially those from multiple sources, are advantageous for building models, it is utmost significant to focus on the robustness of the system rather than its accuracy. A major bottleneck in MRI processing is the dearth of standardization, which affects the uniformity of results across different datasets.

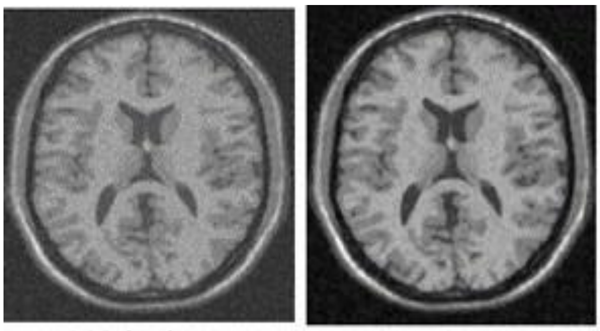
The MRI available for BT patients also tends to be inadequate, noisy, and sometimes mislabelled, with challenges like data redundancy, sparsity, and missing values. These issues should be tackled properly, as small datasets often result in poor approximation during the training phase, which can lead to overly optimistic performance estimates with high variance [2].

A major issue with DL techniques in BT classification is class imbalance. This imbalance, coupled with a limited number of data points, can cause underfitting or overfitting, leading to significant bias during the training phase. Furthermore, the performance evaluation process becomes problematic.

Incorporating data from other imaging modalities, like Diffusion Tensor Imaging (DTI), could lead to significant improvements in CNN architectures. These advancements may facilitate the development of automated cancer segmentation systems, potentially enhancing clinical decision-making by providing doctors with more accurate diagnostic support [54].

IV. General DL Methodology for Detection and Classification

***Data Preparation*:** The MRI were taken from Kaggle website. This dataset comprises 5712 MRI. The data was divided into 3 parts. 3998 MRI for training, while the second set of 1143 MRI is for validation. Rest 571 MRI was used for testing. The actual images from a MRI scan may include a lot of extraneous and unnecessary information [34]. The noise in the images was mitigated with a Gaussian blur filter, which smoothed the visuals but preserved significant details [2,4,13]. Subsequently, a high-pass filter was applied to refine sharpness and uncover complex features. Fig. 1 depicts the noisy MRI and pre-processed denoised image. The images are normalized to standard network size 224*224 pixel. All the of MRIs were initially pre-processed to have the same size [54].



a) Noisy image b) Denoised image

Fig.1. Example of a MRI a) noisy b) pre-processed denoised image.

Data augmentation: To increase the size of data augmentation approaches have been used [8,12,15,21]. Image augmentation is used on training data. The original dataset is transformed to extend the training dataset, producing more data. It is ensured that new data is useful and not just a superfluous increase in volume. Conventional data augmentation method of geometric transformations - flipping, rotation, shearing, rescaling – was done. Now training set is of 11994 MRI.

Model architecture: This research is based on two models – a) customised CNN (CCNN) as well as b) customised YOLOv8 (Henceforth known as CY8) techniques [3,55]. Fig2 shows the model. The training and testing phase blocks are changed for CCNN and CY8 models. Rest of the blocks remain the same.

A CCNN model for BTC is specifically designed to identify and classify tumors with high accuracy. The customization includes optimizing hyperparameters, adding specialized layers, to address the nuances of tumor morphology. The proposed CCNN comprises alternating Conv2D and MaxPooling2D layers to extract features from MRI scans. It includes four Conv2D layers and four MaxPooling2D layers. The ninth layer is a flattening layer that transforms the 2D output into a 1D tensor. Tenth was the fully connected three Dense layers. To introduce non-linearity the ReLU activation function is used [39-41]. ReLU-activated segments of 3096, 1200 and 512, respectively was used [38,42,44]. Each layer with ReLU activation allowed the model to learn intricate patterns of the input data. This helped in getting high accuracy and performance.

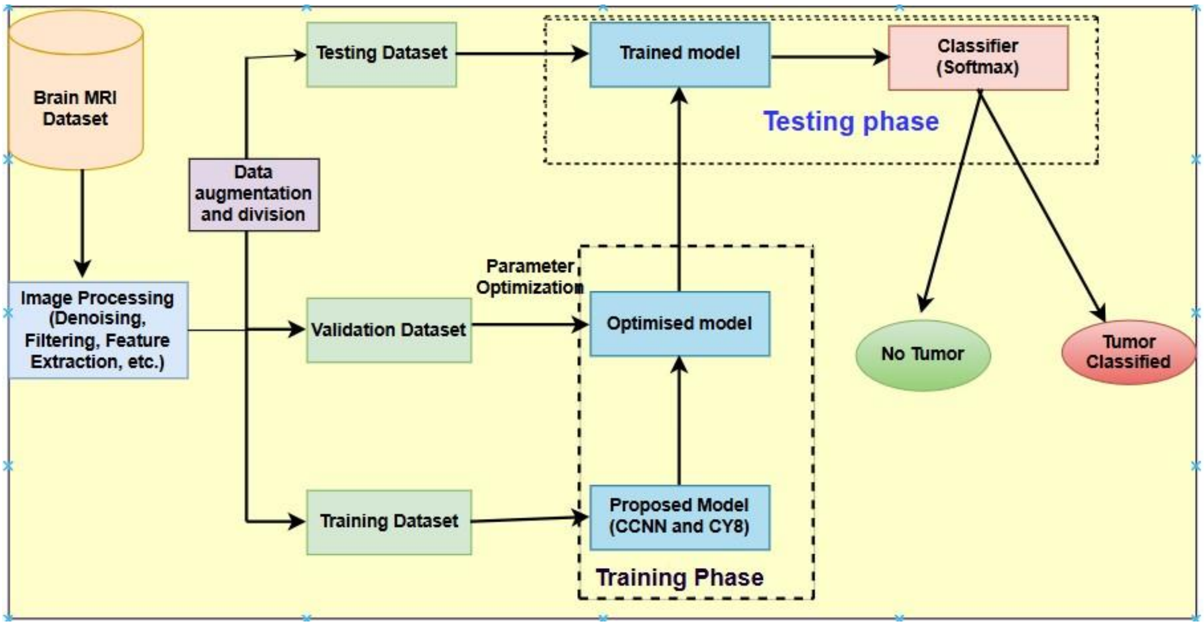


Fig.2. Methodology for detecting and classification of BT

The customization in CY8 is done by altering the architecture, adjusting hyperparameters, and selectively retraining certain layers while freezing others. This constitutes the base model. YOLOv8 by Ultralytics [3 ,55] is made of 03 fundamental parts: Backbone, Neck, and Head [3].
Backbone – Functions as a deep learning-driven feature extractor for the input image.
Neck – Combines feature representations from multiple Backbone layers to refine detection.
Head – Outputs the final predictions by identifying object classes and their bounding boxes. Figure 3 shows the internal structure of YOLOv8 [55]. This is used in the training phase of proposed model of figure 2 for implementing CY8.

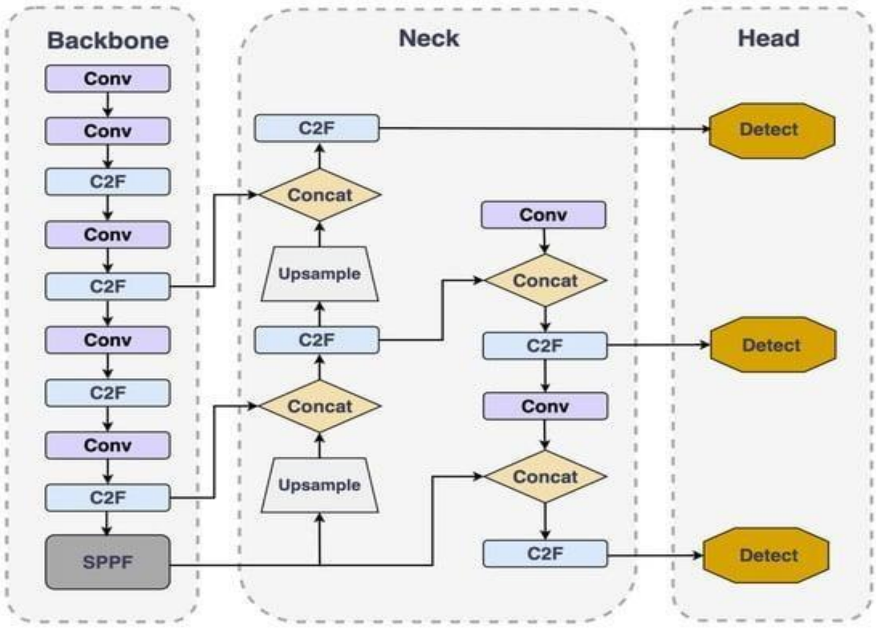


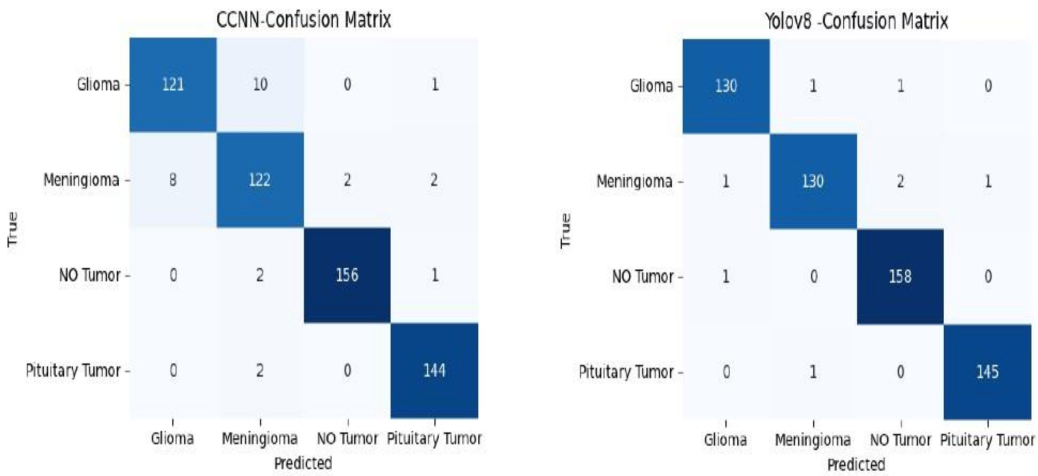
Fig.3. YOLOv8 Architecture [55]

Training and Testing: The data is organized into separate clusters, distributing 70% for testing, 20% for validation, and 10% for training. Validation set aids in hyperparameter tuning and performance monitoring during model development [13,16]. This concept of partitioning ensures robust evaluation and optimization of the DL model for BT detection and classification [33, 41]. Every model underwent 80 epochs (iterations) of training. Nadam was used as an optimiser for all the architectures. Table II gives the Hyper parameter for training. A Dropout layer is introduced for regularization, randomly nullifying 45% of the inputs during training. This method aids in reducing overfitting and strengthens generalization performance. To stop overfitting, techniques such as batch normalization, dropout, and regularization are incorporated throughout the architecture [12-18].

Evaluation of the model: Analyse the trained model with the testing and validation datasets. This is done to determine how effectively it will function in practical situations. Evaluation criteria like accuracy, precision, recall, is utilized [54].

V. Results and Discussion

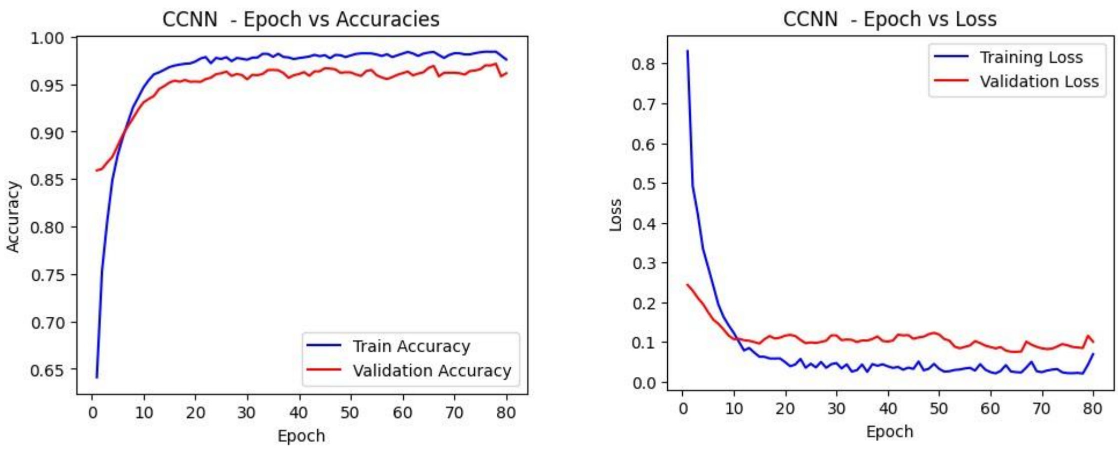
The performance Confusion matrix (CM) of the models is presented here in figure 4.



a) b)

Fig. 4. a) CCNN Model CM b) CY8 model CM

CCNN model: Fig 5a. and 5b shows the accuracy and loss curves for the CCNN model. As the difference amid training and validation curves is slight, suggesting that it is generalizing well. The train accuracy is 98.23% whereas it is 96.98 % for validation.



a) b)

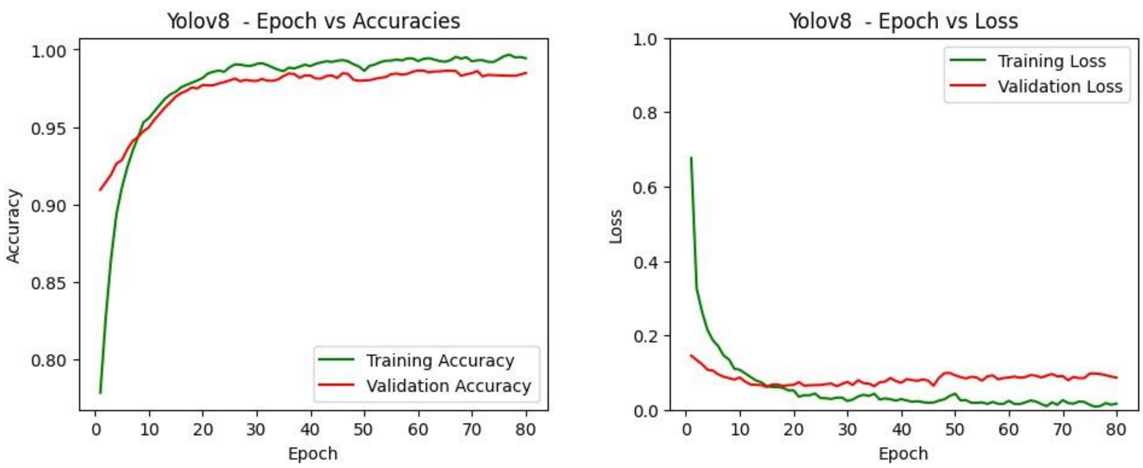
Fig. 5. a) CCNN accuracy plots b) CCNN loss plots

The table II gives the test accuracy and specificity of the CCNN model. Overall, the model executes well across all BT classes, with "No tumor" class achieving the highest accuracy and specificity, followed closely by "Pituitary tumor."

TABLE II. CLASS REPORT CCNN MODEL

Tumor Class	Test Accuracy	Specificity	Precision	Recall	F1 score	Support
Glioma tumor	0.9667	0.9818	0.9380	0.9167	0.9272	132
Meningioma	0.9545	0.9680	0.8971	0.9104	0.9037	134
No tumor	0.9812.	0.9951	0.9873	0.9811	0.9842	159
Pituitary tumor	0.9735	0.9906	0.9730	0.9863	0.9796	146

CY8 model (based on YOLOv8): Fig 6a and 6b shows the accuracy and loss curves for the CY8 model. Slight difference between training and validation curves advocates that it is generalizing well. The train accuracy is 99.45% whereas for validation it is 99.08%.



a) b)

Fig. 6. a) CY8 model accuracy plots b) CY8 model loss plots

The table III gives the test accuracy and specificity of the CY8 model. The CY8 demonstrates excellent performance in all classes, as evinced by high precision and recall scores. Overall, this CY8 model performs exceptionally well, with minimal misclassifications. This high level of performance suggests that the YOLOv8 is well-matched for practical applications in identifying different types of BT.

TABLE III. CLASS REPORT CY8 MODEL

Tumor Class	Test Accuracy	Specificity	Precision	Recall	F1 score	Support
Glioma tumor	0.9877	0.9932	0.9771	0.9697	0.9734	132
Meningioma	0.9895	0.9954	0.9848	0.9701	0.9774	134
No tumor	0.9912	0.9903	0.9755	0.9937	0.9844	159
Pituitary tumor	0.9895	0.9929	0.9795	0.9795	0.9795	146

VI. CONCLUSION

Ensuring precise classification of BTs is essential in healthcare. This review analyses 53 modern systems that utilize DL and ML for diagnostic purposes. A wide array of BTC architectures, designed for single and multiple data sources, is employed by the systems as reviewed in this paper. A comprehensive enumeration of dataset sources is provided in this paper to facilitate understanding and usage by the research community. It is evident from the paper how technological advancements are being harnessed to improve precision and accuracy.

With less training samples, the CCNN system showed an overall test accuracy of 96.89% while YOLOv8 based CY8 model achieved 98.94% accuracy in test phase. The CY8 model demonstrates excellent performance across all tumor classes.

Additionally, this manuscript provides insights into prevalent MRI datasets for research on BTs. Though many DL methodologies exist for classification endeavours, CNN proves especially adept at categorizing BT as seen from literature. YOLOv8 outperformed CCNN by achieving higher accuracies, a factor that is crucial for effective BT diagnosis. Continuous improvements and promising outcomes highlight the vital role of YOLO architectures. With ongoing collaboration between researchers and clinicians, the future for YOLO-based applications in BT classification is very promising.

Conflict of Interest

The authors confirm no conflicts of interest concerning the current study.

AUTHOR CONTRIBUTIONS:

Conceptualization, methodology and investigation V.V.; writing—original draft preparation, V.V.; writing—review and editing, V.V. and A.A; All authors have read and agreed to the published version of the manuscript.

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