
ISSN: 2321-2152
IJMECE
International Journal of modern electronics and communication engineering
E-Mail
editor.ijmece@gmail.com
editor@ijmece.com
www.ijmece.com

ISSN 2321-2152
www.ijmece.com
Vol 13, Issue 2, 2025

MRI-BASED BRAIN TUMOR DIAGNOSTICS USING ADVANCED AI TECHNIQUES

T Shravan Kumar
Assistant Professor
Computer Science and Engineering (Data-Science)
Sphoorthy Engineering College (JNTUH)
Hyderabad, India
Shravankumart7@gmail.com

Jadhav Swapna
Computer Science and Engineering (Data-Science)
Sphoorthy Engineering College (JNTUH)
Hyderabad, India
swapnajadhav2004@gmail.com

Ponugoti Vardhini
Computer Science and Engineering (Data-Science)
Sphoorthy Engineering College (JNTUH)
Hyderabad, India
Vardhini2304@gmail.com

M V Y Narasimham
Computer Science and Engineering (Data-science)
Sphoorthy Engineering College (JNTUH)
Hyderabad, India
mvynarasimham03@gmail.com

Nakkala Lokesh Reddy
Computer Science and Engineering (Data-Science)
Sphoorthy Engineering College (JNTUH)
Hyderabad, India
Lokereddy790@gmail.com

Abstract: Long-term brain injury results from aberrant proliferation of either malignant or non-malignant brain tissues. One of the most used techniques for identifying brain tumors is “magnetic resonance imaging (MRI)”. Experts physically inspect MRI filters to assess if a patient has a brain tumor. However, subjective interpretations might lead to conflicting outcomes when MRI scans are analysed by several specialists. The work uses a combination of Vision Transformers, ensemble models, and transfer learning techniques to investigate datasets for brain tumor detection and classification. Algorithms like “TL-VGG16, TL-InceptionV3, TL-NASNetMobile+NASNetLarge, VisionTransformer-SWIN, and VisionTransformer-CCT” are used for categorization. With an accuracy of 99.7%, “TL-NASNetMobile+NASNetLarge” performed the best out of all of them. Detection models such as “Yolo v5s6, Yolo v8, and Yolo v9” are used, and datasets are investigated by reading and graphing photos. Yolo v8 had a “mean average precision (mAP)” of 81.3%, which was better than the others in detection. The method uses explainable AI to guarantee more reliable and consistent outcomes in the identification and categorization of brain tumors.

***“Index Terms** - Brain Tumor Detection, MRI Imaging, Vision Transformers, Transfer Learning, Yolo v8, Explainable AI”.*

1. INTRODUCTION

Excessive brain cell proliferation is a hallmark of a brain tumor, which frequently leads towards major health issues like morbidity and, in certain situations, cancer-related illnesses. Malignant tumors cause more aggressive damage because they penetrate surrounding brain tissue & multiply rapidly. Tumors can endure classified as either non-malignant or malignant. Metastatic brain cancer, another name for secondary brain tumors, starts in another part of the body & spreads towards the brain, which is a common place for metastases. Lung, breast, skin (melanoma), colon, kidney, & thyroid cancers abide among the common primary tumors towards spread towards the brain. About 787,000 people in the US receive a brain tumor-related diagnosis each year, according towards the National Brain Tumor Association, highlighting the vital need for early detection & precise diagnosis [1].

One of the most popular methods for detecting brain tumors is magnetic resonance imaging (MRI), especially before & during surgery. Clinical decision-making has been greatly improved through extremely extensive, non-invasive imaging of MRI, which provides important information for the medical plan. MRI is different from traditional imaging methods such as CT scans, which abide less successful in distinguishing between different types of brain tissue, where it can distinguish soft tissue in three dimensions. Recent developments in MRI technology have made it possible towards testify & mark the human brain accurately, which has helped among accurate identification & evaluation of brain tumors. According towards studies, MRI is a great tool for tumor shape, location & joining among adjacent structures - all abide important for diagnosis & medical plan [2].

In order towards increase the accuracy & effectiveness of identifying brain tumors using MRI scans, many intensive learning methods have been investigated. For example, Znet, a deep learning network for 2D MR tumor segmentation, has promised segmentation of brain tumor detection skills [3]. In addition, through focusing on the most relevant aspects of MRI scanning, machine learning models that include the attention mechanisms appear towards improve the accuracy of the brain tumor division [4]. In addition, MR images have increased the use of transfer setting towards identify brain cancer. Research indicates that pre -trained models adapted towards identify brain tumors perform better than traditional techniques. Deep transmission learning techniques have been used successfully towards change models as a skill network towards detect more accurately through brain cancer [5]. This development shows how MRI imaging & condition Deep learning models can endure used towards improve clinical skills & towards offer more accurate tumor identification & classifications.

Therefore, the use of deep learning models has improved the identification & classification of brain tumors from MRI scans, providing encouraging benefits in clinical results & clinical precision.

2. RELATED WORK

With several developments targeted towards increase clinical results & clinical accuracy, the use of deep teaching algorithms for the identification & division of brain tumors has recently attracted a lot of attention. Intensive analysis of deep learning - based techniques for the division of the brain tumor was presented through Liu et al. [4]. The capacity of the convolutional neural network (CNN) was highlighted towards automate the division of brain tumors from the MRI scan when they had examined several architecture & function. His research established the basic work towards understand the application of a deeper learning model for identifying tumor in medical imaging & a challenging job among division.

A deep teaching model designed for the division & analysis of brain tumors was specifically presented through Chahal et al. ,. His research focused on using condition -of -art learning methods, especially CNN towards increase the division's accuracy & efficiency. He showed that deep learning models can perform better when it comes towards partition quality compared towards traditional imaging techniques, & offers more reliable ways towards identify brain tumors. The importance of deep learning towards improve the functionality of medical image analysis equipment was further shown through this task.

In another contribution, Abdulbaki et al. [[] The extended calculation towards estimate the amount of brain tumors is focused on computed tomography (CT) scanner paintings. Their techniques can endure used for MRI data towards detect brain tumors, even though their main focus was on CT images. He presented a method for assessing the amount of tumors using the machine learning algorithm, which is necessary towards determine how far among a tumor & develop effective treatment plans. His research acts as an excellent example of how towards use machine learning methods in clinical surroundings towards increase the treatment plan & clinical processes.

Using X -ray paintings in the chest, Sethi et al. [9] Proposed an intensive learning-based diagnostic recommendation system for COVID-19. Although their research was focused on detecting COVID-19, brain tumors detection can greatly benefit from techniques that they used towards use for deep learning for medical imaging. More & more important now is the interdomain transfer of knowledge between areas of medicine, like from MRI scans of brains towards X-rays of chests. Their technique, adaptable for finding brain tumors, involves the use of convolutional neural networks (CNNs) towards identify automatically anomalies in medical images.

In order towards improve the model's performance & increase its capacity towards identify pneumonia in chest X-rays, Militante et al. [10] introduced an adaptive deep learning model for pneumonia detection using CNNs. Their method of modifying CNNs for better image analysis can endure used towards detect brain malignancies in MRI images, even though their study has nothing towards do among brain tumors specifically. In the realm of medical imaging, where performance can endure significantly improved through fine-tuning models towards particular diagnostic tasks, the idea of adaptive learning is essential.

In the age of deep learning, Hussein et al. [11] investigated new supervised & unsupervised learning techniques for the characterization of pancreatic & lung cancers. Their study showed how cancer can endure described in many organs, including the brain using a combination of monitored & unsafe learning. through using trained transmission models in sufficient data sets among medical images, this work emphasizes the opportunity towards integrate more deep learning methods towards improve the classification of tumors, not only for lungs & abuse in the pancreas, but also for brain tumors.

towards improve the skills of the model detection, Bar et al. [12] Use deep learning towards detect breast pathology, focusing on non-medical training techniques. This method is especially remarkable because it examines the possibilities of implementing generalized deep learning models in medical image processing, & challenges traditional dependence on specific training data for the medical field. through using non-medical deep learning models that have been trained on large versions of general medical data, their work can endure expanded towards detect brain tumors, increasing the use of AI in medical diagnostics.

The methods of learning advanced machine towards analyze human behavior in the context of cognitive data processing were proposed through LV et al. [13]. Their work on cognitive data processing & machine learning can help develop an AI system for medical diagnosis, although their primary attention was behavioral analysis. The combination of medical image analysis & human behavioral analysis models can provide a new approach towards clinical decision -making, especially when it comes towards understanding how AI system diagnoses among MRI scan.

A combination -based deep learning model was presented through Noren et al towards diagnose brain tumors. [14]. His research focused on combining several deep teaching models towards increase the accuracy & flexibility of detection of brain tumors. Better functional extraction from MRI images was made possible through the composition technique, which is necessary towards detect & increase the functionality of the classification model. His research clarified how important it is towards use multimodel techniques towards improve the ability of deep teaching systems for medical image interpretation.

Bhuvaneshwari [15] used the Convolutional neural Network (CNN) on MRI images towards develop an automated method for the brain tumor. Their research has shown that CNNs abide able towards detect & classify brain cancer accurately & automatically. through using CNN for automated division, the identity of brain tumors becomes more efficient & becomes less dependent on human participation. In the study of Bhuvaneshwari, the medical image combines the expansion of research on the use of deep teaching techniques towards increase the accuracy & speed of the division.

Overall, these tasks show the remarkable progress made in the use of deep learning models for the detection & classification of the brain - especially CNN & other sophisticated machine learning techniques. The promise of these techniques towards improve the accuracy, efficiency & dependence of brain tumor diagnosis is postponed through today's research, which will eventually lead towards better clinical results & patient care. The use of state-of-the-art algorithms, like deep transfer learning & adaptive learning approaches, continues towards open up the boundaries of medical image analysis's promise, especially regarding brain tumors.

3. MATERIALS & METHODS

The proposed system applies explainable AI & deep learning methodologies towards improve the detection & classification of brain tumors. The system employs an array of leading-edge classification models, including "VGG16, VGG19, Inception V3, ResNet50, Inception ResNetV2, Xception, & Vision Transformer (ViT)". Accurate diagnosis is made possible through these models' training towards distinguish between distinct tumor kinds. These classifiers' capabilities abide combined in an ensemble model called IVX16 towards improve performance & lower mistakes. In order towards identify & locate tumor abnormalities in MRI scans, the system incorporates YOLO-based models, including "YOLOV5x6, YOLOV5s6,

ISSN 2321-2152
www.ijmece.com
Vol 13, Issue 2, 2025

YOLOV8n, & YOLOV9n”. towards provide reliable processing of the MRI data, the “NASNetMobile & NASNetLarge models” abide also used for feature extraction & dataset analysis. Medical practitioners can better comprehend the logic behind the system's predictions & have more faith in automated diagnosis when explainable AI approaches abide used towards produce visible, interpretable outcomes.

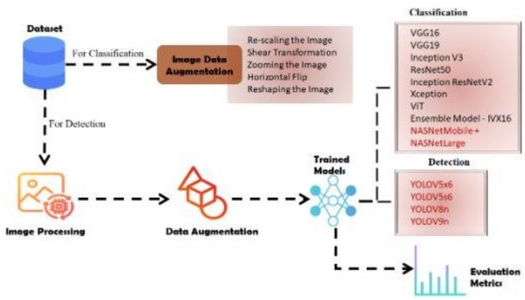


Fig.1 Proposed Architecture

The figure (Fig. 1) shows the system architecture. This system uses a variety of methods, including as “ensemble models, transfer learning, & Vision Transformers (ViT)”, towards detect & classify brain tumors. towards train different categorization & detection models, the system first processes & enhances the visual data. “VGG, Inception, ResNet, Xception, & ViT” abide among the classification models. The “YOLOv5 & YOLOv8” variations abide used in the detection models. towards improve the robustness & performance of the model, ensemble techniques & transfer learning abide used. Lastly, the system uses the proper metrics towards assess the trained models' performance.

i) Dataset Collection:

Images for both brain tumor classification & detection functions create a dataset used in this study. A total of 5712 images, divided into four separate classes, available for classification; 1311 more images than the same categories abide available for additional analysis. The dataset consists of images that abide read & shown in the detection assignment towards identify tumor sites & properties, providing useful information for both classification & detection functions.

ii) Pre processing:

For both classification & detection functions, pre-proclamation is necessary towards improve the quality & variety of incoming data. It uses methods such as image processing, annotation & growth & scaling for classification & scaling towards find out towards find out.

a) Classification: towards increase model flexibility & avoid overfitting, image data text techniques abide used in the classification function. towards guarantee the same size for the entrance towards the model, images abide first set up. The normalization of the model is improved through using shear change towards introduce small deformities. through mimicking many approaches, zooming increases the adaptation capacity of the model for different image scales. towards give more diversity towards the information, horizontal flipping is used towards reflect images. Finally, replace images that they complete the input specifications of the nerve network & improve performance during exercise.

B) Detection: In order towards prepare data for model training, many imaging techniques abide used in identification work. towards standardize images for use as input in detection models, they first become Blob objects. After defined the path for each image, the boundary box is declared towards identify areas of interest as tumor sites. For effective manipulation, these bounding boxes abide later converted towards a number of matrices. Reading networking & recovering relevant output layers loads the pre -beached model. Image processing

ISSN 2321-2152
www.ijmece.com
Vol 13, Issue 2, 2025

includes scaling images for uniformity in the next steps, switching colour space from BGR towards RGB, adding annotation files towards images & making stitches for places detected. Finally, towards improve model flexibility, methods of data text, including rotation, zooming & random changes, abide used.

iii) Algorithms:

A deeply firm nerve network architecture called VGG16 classifies images using 16 layers. In our efforts, VGG16 learns features from MRI scans towards classify brain tumors. This increases classification accuracy & addiction through identifying specific tumor functions & distinction between benign & malignant cancer.

among 19 layers, VGG19 is an extension of VGG16 which provides increased extraction capacity. VGG19 examines the MR scan & extracts specific painting features for tumor classification. It provides more accurate classification in complex medical images & improves the accuracy of tumor depth discrimination.

The Deep Learning Model Inception V3 is known for its conventional several levels, which makes it possible towards process images of different sizes. This research uses Inception V3 towards classify MR images, which allow accurate detection of tumor type & effective convenience, even in small or complex tumor sites.

The ResNet50 is a residual network that avoids missing gradients using jump connections. It learns high-level functions, which guarantees deep network training, which is used towards classify brain cancer into MRI data. For accurate detection, the recanet50 is excellent in the management of a large dataset among complex tumor patterns.

The beginning of the benefits of ResNet & Inception Architecture is combined in ResNetV2. It uses its ability towards learn both shallow & deep functions towards classify images of brain tumors. The accuracy of identifying different MRI scanning tumor types has increased among this architecture.

A deep fixed model built on a separate convention is called Xception. Xception is used towards classify the tumor through extracting complex information from MRI images in research. It is suitable for detecting minute tumor variation in medical imaging due towards its efficiency in handling spatial features.

For image classification uses VIT transformer architecture, which has long been employed through NLP. In this project, KIT is used towards process MR images such as sequences & classify brain tumors. This image increases the ability towards identify different types of tumors through effectively identifying long -distance relationships between pixels.

towards increase classification accuracy, the improved model-IVX16 contains more models, such as VGG16 & InceptionV3. This model combines the output from several models towards detect tumors, using the benefits of each design towards improve generalization & produce more accurate tumor classification.

Nerve networks NASNetMobile & NASNetLarge abide sewn towards mobile devices & large datasets respectively. These models abide used towards classify brain tumors in MRI images in this study, in real time, excellent accuracy of balanced calculation efficiency for tumor detection & classification.

Algorithms for detection:

ISSN 2321-2152
www.ijmece.com
Vol 13, Issue 2, 2025

The Yolov5 object detection model means a more sophisticated repetition, the Yolov5x6 means too high accurate applications that detect applications. Yolov 5x6 is used in MRI paintings in identifying & detection of brain tumors. The ability towards detect tumors is quickly & accurately guarantees effective tumor identity under clinical conditions.

Yolov5, a more compact & effective version of the Yolov5S6 is designed for sharp processing. among emphasis on speed & real -time analysis, it is used in our project towards identify MR data cancer. The Yolov5S6 works effectively in clinical & mobile environments where early diagnosis is needed.

Another recent version of the Yolov8 family, the Yolov8n is designed towards endure faster & more accurate. It provides extended processing time & accuracy of detection, which is important for rapid tumor diagnosis, & in MRI images used in an attempt towards identify & detect cancer.

A better version of Yolov8 that is further set for identification among high compatibility is called Yolov9n. Our use uses the Yolov9N towards detect tumors in MRI images, allowing for accurate tumor rooms & classification & improves the system's ability towards identify minimal deviations.

4. RESULTS & DISCUSSION

Precision: relationship between events or tests certain abide properly classified towards anyone classified as positive is called accurate. Therefore, there is a formula considering determining accuracy:

$$"Precision = \frac{\text{True Positive}}{\text{True Positive } + \text{False Positive}} (1)"$$

Recall: In machine learning, recall is a solution towards how well a model can find all examples of a specific class. ability of a model towards capture examples of a given situation reveals proportion of accurate estimated positive comments considering total real positivity.

$$"Recall = \frac{\text{TP}}{\text{TP } + \text{ FN}} (2)"$$

mAP: A ranking quality data is the mean average precision (MAP). This takes into account the amount of relevant proposals & where they abide on the list. Average precision (AP) for average precision (Ap) on K for each user or Query is used towards calculate the map on K.

$$"mAP = \frac{1}{n} \sum_{k=1}^{k=n} AP_k (3)"$$

Accuracy: A test ability towards make a proper difference between healthy & sick cases is a measure of accuracy. We can determine accuracy of a test through calculating proportion of cases undergoing proper positivity & genuine negative. It is possible towards express this mathematically:

$$"Accuracy = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} (4)"$$

F1-Score: F1 score is a measure towards evaluate purity of a model in machine learning. It takes memory & accuracy of a model & mixes them. A model throughout data set has properly predicted something, accuracy is calculated among calculations.

$$"F1\, Score = 2 * \frac{Recall \text{ X } Precision}{Recall + Precision} * 100(5)"$$

Table 1 assesses each algorithm's performance parameters, including accuracy, precision, recall, & F1-score. The TL-NASNetMobile & NASNetLarge routinely beat all other algorithms on every metric. The metrics for the other algorithms abide also compared in the tables.

Table (2) assesses each algorithm's performance parameters, including precision, recall, & mAP. The Yolo v8 continuously beats all other algorithms in every metric. Additionally, a comparison of the metrics for the various methods is provided in the tables.

Table.1 Performance Evaluation Table for Data – 1

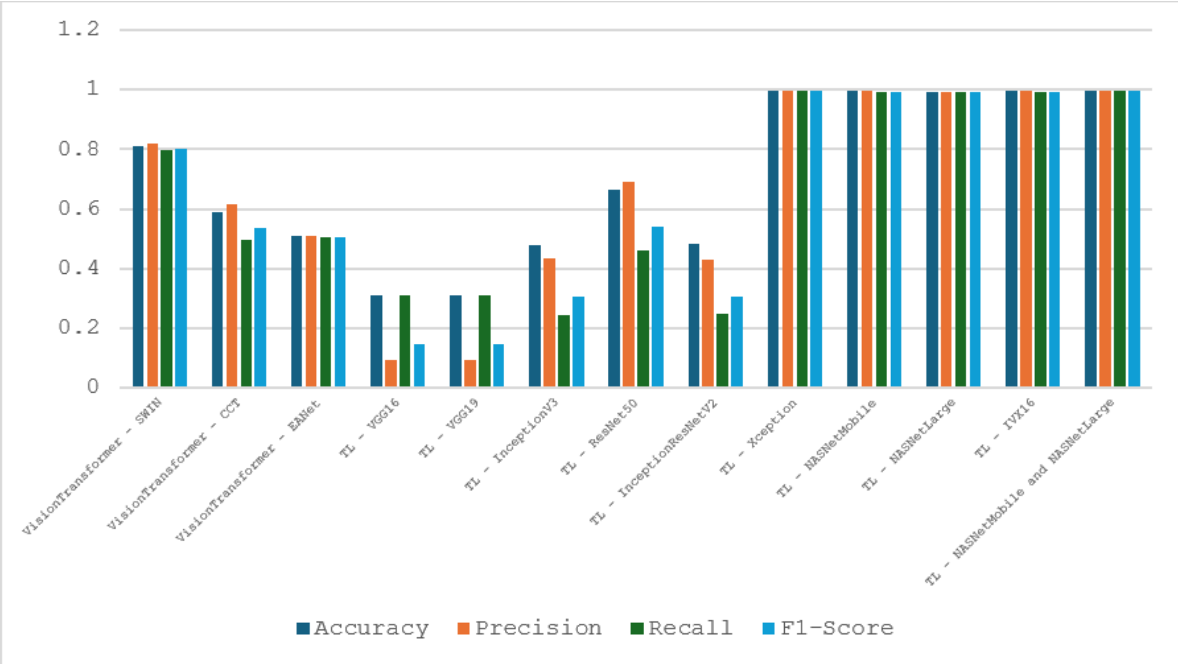
Model	Accuracy	Precision	Recall	F1-Score
VisionTransformer - SWIN	0.811	0.818	0.797	0.804
VisionTransformer - CCT	0.590	0.617	0.495	0.536
VisionTransformer - EANet	0.511	0.511	0.504	0.506
TL - VGG16	0.309	0.095	0.309	0.146
TL - VGG19	0.309	0.095	0.309	0.146
TL - InceptionV3	0.477	0.434	0.245	0.308
TL - ResNet50	0.665	0.689	0.463	0.539
TL - InceptionResNetV2	0.484	0.429	0.247	0.308
TL - Xception	0.995	0.995	0.995	0.995
TL - NASNetMobile	0.995	0.995	0.994	0.994
TL - NASNetLarge	0.994	0.994	0.994	0.994
TL - IVX16	0.995	0.996	0.992	0.994
TL - NASNetMobile and NASNetLarge	**0.997**	**0.997**	**0.995**	**0.996**

Table.2 Performance Evaluation Table for Data – 2

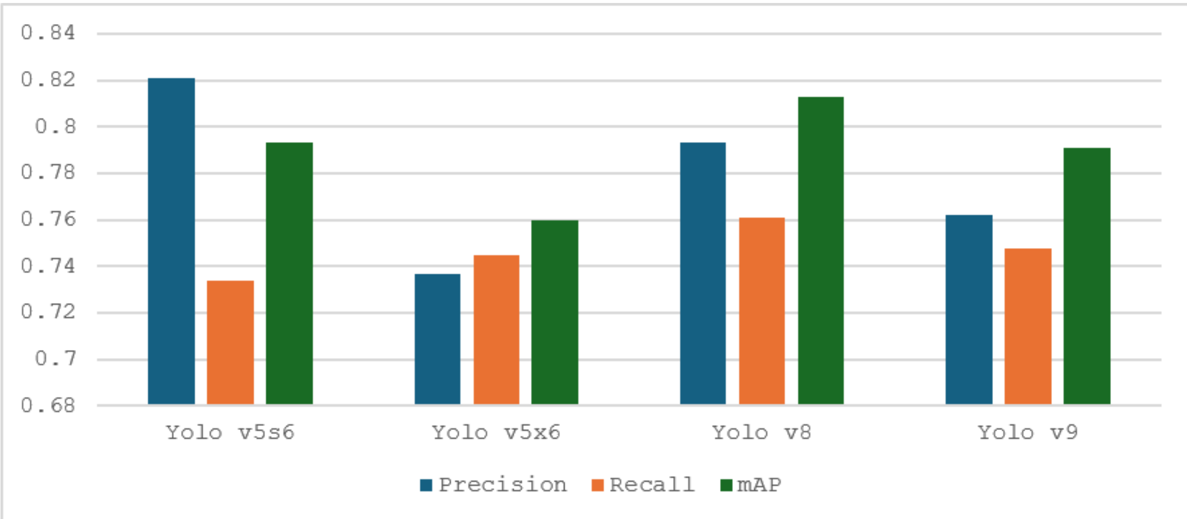
Model	Precision	Recall	mAP
Yolo v5s6	0.821	0.734	0.793
Yolo v5x6	0.737	0.745	0.760
Yolo v8	**0.793**	**0.761**	**0.813**
Yolo v9	0.762	0.748	0.791

Graph.1 Comparison Graphs for Data - 1

ISSN 2321-2152
www.ijmece.com
Vol 13, Issue 2, 2025

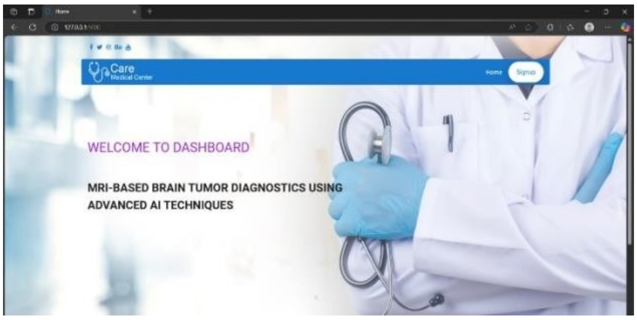


Graph.2 Comparison Graphs for Data - 2



Graph (1) uses the colors blue for accuracy, orange for precision, green for recall, & sky blue for F1score. The TL-NASNetMobile & NASNetLarge for Detection performs better than the other models in every metric, attaining the highest values. These results abide graphically depicted in the graphs above.

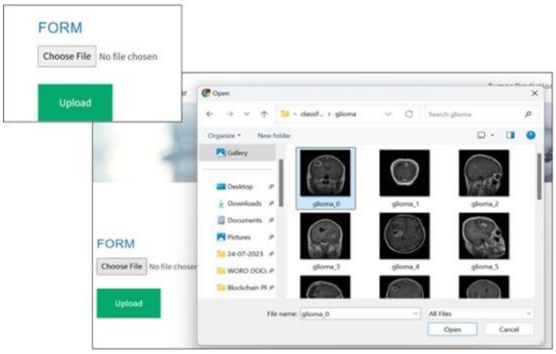
Graph (2) shows mAP in green, recall in orange, & precision in blue. The Yolo v8 for Detection performs better than the other models in every criterion, attaining the highest scores. These findings abide graphically depicted in the graphs above.



ISSN 2321-2152
www.ijmece.com
Vol 13, Issue 2, 2025

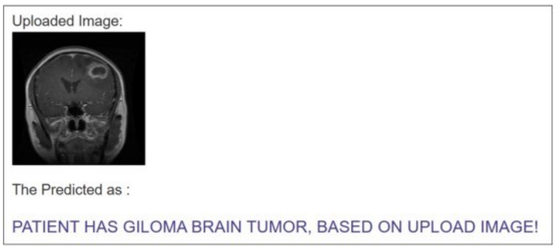
"Fig.2 Home Page"

In the above figure 2, this is a user interface dashboard for brain tumor, it is a welcome message for navigating page.



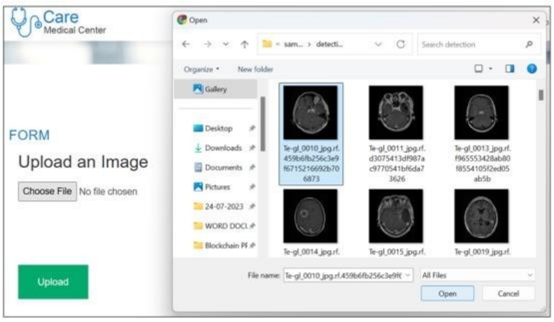
"Fig.3 User input Page"

In the above figure 3, this is a user input page, using this user can upload image for testing.



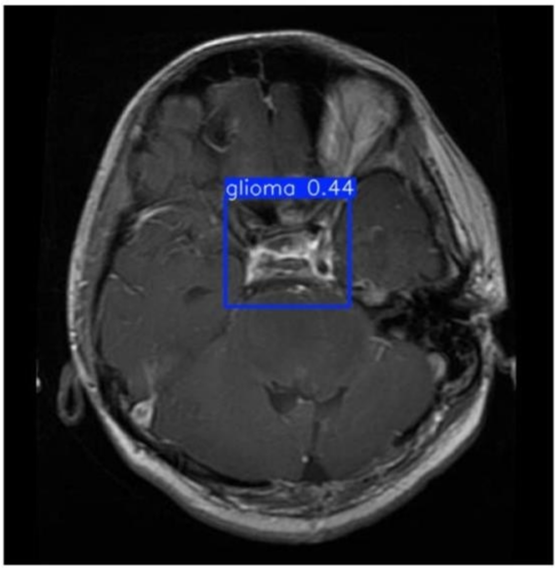
"Fig.4 Classification result"

In the above figure 4, this is a result screen, in this user will get output for loaded input image.



"Fig.5 User input Page"

In the above figure 5, this is a user input page, using this user can upload image for testing.



"Fig.6 Detection result"

In the above figure 6, this is a result screen, in this user will get output for loaded input image.

5. CONCLUSION

In order towards accomplish accurate & effective classification & detection, the investigation concentrated on classifying brain cancers using sophisticated models. among a 99.7% classification accuracy, the "NASNetMobile & NASNetLarge ensemble" showed remarkable performance. These models were chosen because they successfully extract intricate information from MRI pictures, guaranteeing precise tumor type detection. Their combined skills improved the classification process & decreased the inconsistencies that were frequently seen in expert manual evaluations. Yolo v8 proved towards endure the most successful method for detection, among a mean average precision (mAP) of 81.3%. Its exceptional performance demonstrates its ability towards precisely identify brain tumors, making it a dependable option for such applications. The method addresses the shortcomings of conventional techniques & helps among the prompt & accurate identification of brain tumors through utilizing the strengths of “NASNetMobile, NASNetLarge, & Yolo v8”. This guarantees consistent & accurate results. This combination of condition - -species methods highlights the promise of clear AI & deep learning models for important health services.

In order towards enable faster & more accurate diagnosis, future development can focus on connecting "Yolo v8, NASNetMobile, & NASNetLarge" among real -time MR processing systems. Model transparency & clinical adoption can endure expanded through expanding the dataset towards include different types of tumors & improving the clear AI mechanism. In addition, adding multimodal data - such as natural & medical history - can improve the accuracy of detection & classification, leading towards more personal treatment plans.

REFERENCES

[1] M. A. Ottom, H. A. Rahman, & I. D. Dinov, “ZNet: Deep learning approach for 2D MRI brain tumor segmentation,” IEEE J. Transl. Eng. Health Med., vol. 10, May 2022, Art. no. 1800508.

[2] T. M. Ali et al., “A sequential machine learning-cum-attention mechanism for effective segmentation of brain tumor,” Front. Oncol., vol. 12, Jun. 2022.

[3] S. Asif, W. Yi, Q. U. Ain, J. Hou, T. Yi, & J. Si, “Improving effectiveness of different deep transfer learning-based models for detecting brain tumors from MR images,” IEEE Access, vol. 10, pp. 34716–34730, 2022.

[4] H. A. Shah, F. Saeed, S. Yun, J.-H. Park, A. Paul, & J.-M. Kang, “A robust approach for brain tumor detection in magnetic resonance images using finetuned EfficientNet,” IEEE Access, vol. 10, pp. 65426–65438, 2022.

[5] M. Rizwan, A. Shabbir, A. R. Javed, M. Shabbir, T. Baker, & D. Al-Jumeily Obe, “Brain tumor & glioma grade classification using Gaussian convolutional neural network,” IEEE Access, vol. 10, pp. 29731–29740, 2022.

[6] Z. Liu et al., “Deep learning based brain tumor segmentation: A survey,” Complex Intell. Syst., vol. 9, no. 1, pp. 1001–1026, 2020.

[7] E. S. Chahal, A. Haritosh, A. Gupta, K. Gupta, & A. Sinha, “Deep learning model for brain tumor segmentation & analysis,” in Proc. IEEE 3rd Int. Conf. Recent Develop. Control, Autom. Power Eng., 2019, pp. 378–383.

[8] H. S. Abdulbaqi, K. N. Mutter, M. Z. M. Jafri, & Z. A. Al-Khafaji, “Estimation of brain tumour volume using expanded computed tomography scan images,” in Proc. IEEE 23rd Iranian Conf. Biomed. Eng. 1st Int. Iranian Conf. Biomed. Eng., 2016, pp. 117–121.

[9] R. Sethi, M. Mehrotra, & D. Sethi, “Deep learning based diagnosis recommendation for COVID-19 using chest X-rays images,” in Proc. IEEE 2nd Int. Conf. Inventive Res. Comput. Appl., 2020, pp. 1–4.

[10] S. V. Militante, N. V. Dionisio, & B. G. Sibbaluca, “Pneumonia detection through adaptive deep learning models of convolutional neural networks,” in Proc. IEEE 11th Control Syst. Graduate Res. Colloq., 2020, pp. 88–93.

[11] S. Hussein, P. Kandel, C. Bolan, M. B. Wallace, & U. Bagci, “Lung & pancreatic tumor characterization in the deep learning era: Novel

supervised & unsupervised learning approaches," IEEE Trans. Med. Imag., vol. 38, no. 8, pp. 1777–1787, Aug. 2019.

[12] Y. Bar, I. Diamant, L. Wolf, S. Lieberman, E. Konen, & H. Greenspan, "Chest pathology detection using deep learning among non-medical training," in Proc. IEEE 12th Int. Symp. Biomed. Imag., 2015, pp. 294–297.

[13] Z. Lv, L. Qiao, & A. K. Singh, "Advanced machine learning on cognitive computing for human behavior analysis," IEEE Trans. Comput. Social Syst., vol. 8, no. 5, pp. 1194–1202, Oct. 2021.

[14] N. Noreen, S. Palaniappan, A. Qayyum, I. Ahmad, M. Imran, & M. Shoaib, "A deep learning model based on concatenation approach for the diagnosis of brain tumor," IEEE Access, vol. 8, pp. 55135–55144, 2020.

[15] M. Bhuvaneswari, "Automatic segmenting technique of brain tumors among convolutional neural networks inMRI images," inProc. IEEE 6th Int. Conf. Inventive Comput. Technol., 2021, pp. 759–764.