Detection of Brain Tumors Using Advanced Image Processing and the Ensemble Model and YOLO Family

P. Poorna Priya and N. Vidhya Sree
Department of Electronics and Communication Engineering, DIET, Anakapalle, Visakhapatnam, Andhra Pradesh, India

Keywords: You Only Look once, CNN, Image Processing, Brain Tumor, Machine Learning, Deep Learning, Tumor Detection, Classification.

Abstract: Effective diagnosis and therapy of brain tumors depend on their identification and classification. Using the Brain Tumor dataset, this study makes use of sophisticated transfer learning models and deep convolutional neural networks (DCNNs). When models like DCNN, ResNet152, EfficientNetB2, Exception, and Nonmobile were tested, an ensemble of Exception and Nonmobile produced the best accuracy (98.1%). Grade 0 (no malignancy) to Grade III (big tumor) were the four grades into which tumors were divided. With a mean average precision (map) of 78.9%, YOLOv9 fared better than other models for anomaly detection. A Flask-based interactive interface was created for safe and easy access in order to improve usage.

1 INTRODUCTION

Unusual cell growths in the brain called brain tumors raise the pressure inside the skull, impairing essential processes including movement, speech, and thought. They are categorized as either malignant (aggressive, fast-growing, and invasive) or benign (slow-growing, less invasive), and early identification is essential for successful treatment. Conventional diagnosis uses MRI and CT scans, which need to be interpreted by experts and can be laborious and error-prone. Improvements in deep learning (DL), especially convolutional neural networks (CNNs), and artificial intelligence (AI) have greatly enhanced tumor categorization and detection (Kumar et al., 2022; Ullah et al., 2022; Babu Vimala et al., 2023). Better patient outcomes result from these models increased diagnostic precision, accelerated analysis, and support for early action. In order to increase precision, effectiveness, and clinical decision-making, this study investigates the use of deep learning and machine learning for automated brain tumor identification (Mathivanan et al., 2024; Das & Goswami, 2024).

2 RELATED WORKS

MRI scans have been used in a number of researches to investigate AI and deep learning methods for brain tumor identification. Asif et al. used pre-trained CNN architectures such as VGG16, Reset, and Inception to introduce transfer learning-based models and show increased classification accuracy. By improving CNN models and focusing on feature extraction for improved tumor classification, Srinivas et al. further improved this methodology. CNN-based transfer learning was used by Bairagi et al., who demonstrated how effective it is at processing intricate medical images. In order to improve detection accuracy with little data, Anjum et al. optimized pre-trained networks using ResNet50 and InceptionV3. By comparing several CNN models, Khaliki and Başarslan were able to verify that transfer learning performed better in terms of classification accuracy and computational efficiency than traditional three-layer CNNs. By combining DenseNet169 with machine learning classifiers such as Random Forest and SVM, Khan et al. developed Crossover NET, which improved tumor classification. CNNs and transfer learning were integrated by Incir and Bozkurt, who showed enhanced performance on sizable and varied datasets. In order to highlight the significance of flexible AI models in medical imaging, Sadad et al. expanded deep learning

Priya, P. P. and Sree, N. V.
Detection of Brain Tumors Using Advanced Image Processing and the Ensemble Model and YOLO Family.
DOI: 10.5220/0013939700004919

In *Proceedings of the 1st International Conference on Research and Development in Information, Communication, and Computing Technologies (ICRDICCT'25 2025) - Volume 5*, pages 628-633
ISBN: 978-989-758-777-1

applications to multi-class tumor classification (benign, malignant, and metastatic) using VGGNet and ResNet.

3 MATERIALS AND METHODS

The proposed brain tumour detection and characterization framework fosters areas of strength for a for-brain tumour identification and grouping by utilization of a Brain Tumour dataset. To further develop grouping accuracy, the framework totals “deep convolutional neural networks (DCNNs)” with cutting edge move learning models. It uses a half breed model of DCNN and ResNet152 serving as the baseline for growth grouping, utilizing modern models like "DCNN, ResNet152, EfficientNetB2, Exception, and Nonmobile." The four forms of cancer are classified as "Grades 0 (no tumor), Grade I (little tumor), Grade II (medium-sized tumor), and Grade III (big tumor)”. To detect abnormalities in brain scans, the invention makes use of cutting-edge YOLO models, such as "YOLOv5x6, YOLOv5s6, YOLOv8, YOLOv9."These models are trained and optimized to enable precise cancer identification and classification. Incorporated utilizing a Flask based intelligent point of interaction, this offers an easy to understand stage for clinical applications and safe client recognizable proof. Figure 1 shows The Proposed Architecture.

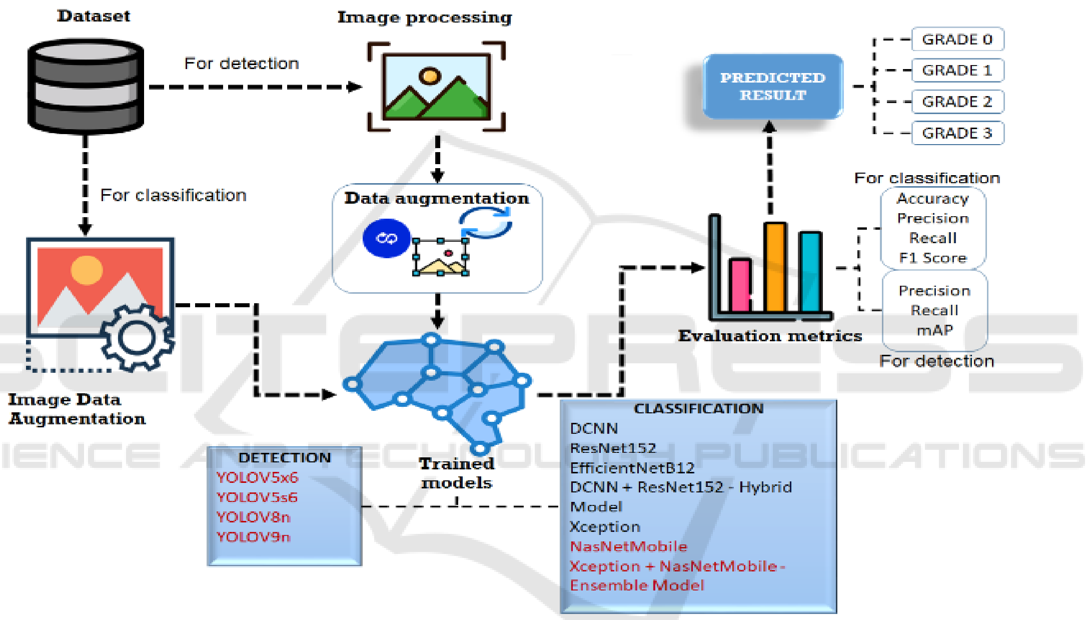

Figure 1: The proposed architecture.

By integrating data augmentation, image processing techniques, and deep convolutional neural networks (DCNNs) for object detection and picture sequencing, this architecture (fig.1) develops a deep learning-based framework for image analysis. Utilizing YOLO models “YOLOv5x6, YOLOv5s6, YOLOv8n, and YOLOv9n” the identification module exactly distinguishes objects inside pictures. The framework makes use of cutting-edge models for characterization, such as "ResNet152, EfficientNetB2, Exception, and Nonmobile," in addition to a proprietary cross-breed model that combines "DCNN and ResNet152 and an outfit model that combines Exception and Nonmobile." Using metrics such as "mean Average Precision (map), F1-score, recall, accuracy, and precision, “execution is entirely surveyed areas of strength for ensuring across both recognition and characterization errands.

3.1 Dataset Collection

MRI images which fall into both harmless and threatening tumour classes - make up the dataset utilized for brain tumour detection and arrangement. Publically available clinical picture files remembering the Brain Tumour Dataset for Kaggle give the dataset and there are many named MRI scans that are pre-handled to guarantee uniformity in size and quality. A complete rationale for model training is provided by the division of the data into several growth grades: "Grade 0 (no tumour), Grade I (small), Grade II (medium), and Grade III (big)".

3.2 Pre-Processing

3.2.1 Classification

Augmenting Image Data: Enhancement of image data for characterization refers to different methods designed to work on the dataset and then increase model guesswork. Re-scaling the picture to normalize the size, shear changes to add minor mathematical bends, zooming in to get better subtleties, and level flips to duplicate a few survey points. Changing the picture likewise ensures consistency in extents, so empowering great preparation. These strategies together increment the dataset and empower the model to more readily oversee variances in genuine visual data.

3.2.2 Detection

Image Processing: Image processing for detection comprises in a few significant stages intended to prepare the information for model surmising. To normalize the picture for input, it initially gets transformed into a mass item. The class is hence determined; next comes announcing the jumping box for detection. To simplify dealing with, the picture is transformed into a NumPy array. The organization layers are perused for stacking the pre-trained model and result layers are separated. Added are the picture and explanation records, which make an interpretation of BGR to RGB, produce a veil, and resize the image to fit the information particulars for the model.

3.2.3 Data Augmentation

In detection, data augmentation alludes to strategies that further develop the summing up limit of the model. To start with, the picture is randomized to add preparing changeability. Arbitrary pivots then, at that point, are utilized to imitate different directions, consequently directing the model to learn invariant properties. To additionally fluctuate datasets, picture changes including mutilation, interpretation, or scaling are likewise finished. These expansion methods ensure the model's capacity to productively recognize objects from a few points, positions, and circumstances, consequently fortifying its presentation and strength in reasonable settings.

3.3 Algorithms

3.3.1 For Classification

DCNN: Deep elements from brain tumour pictures are extricated utilizing DCNN, which gains muddled examples and isolates harmless from cancer cases along these lines empowering dependable tumour grouping.

ResNet152: Reset 152 is utilized since it can oversee deep neural networks, consequently working on the limit of the model to learn and classify growth photographs with higher accuracy by residual learning methods.

EfficientNetB2: Utilizing its adaptable engineering to deal with brain tumour pictures with less boundaries and quicker training times, EfficientNetB2 is utilized to amplify arrangement accuracy while safeguarding effectiveness.

DCNN + ResNet152 - Hybrid Model: Meaning to involve the two plans' assets for further developed highlight extraction and more prominent accuracy in distinguishing brain tumour pictures, the crossover model mixes DCNN and ResNet 152.

Exception: Exception's powerful convolutional design assists the organization with extricating undeniable level data from growth pictures, hence giving improved characterization results to brain tumour identification.

NasNetMobile: Especially accommodating for brain tumour picture examination with restricted assets, Nonmobile gives lightweight execution while keeping up with extraordinary grouping accuracy, thus empowering successful component extraction in versatile settings.

Exception + NasNetMobile - Ensemble Model: Consolidating "Exception with NasNetMobile" permits the group model to take utilization of the two organizations' advantages, subsequently further developing arrangement accuracy by joining different component separating powers from the two models.

3.3.2 For Detection

YoloV5x6: Through continuous item discovery abilities, YOLOv5x6 gives rapid handling and precise distinguishing proof of cancer regions, consequently empowering identification of irregularities in brain tumor images.

YoloV5s6: More modest tumor regions can be successfully distinguished utilizing YOLOv5s6, which ensures quicker execution for constant applications and jelly extraordinary accuracy in anomaly recognition.

YoloV8: On account of its extended engineering and component extraction strategies, YOLOv8 is utilized for refined discovery occupations; it offers higher accuracy and speed in growth finding, especially in confounded pictures.

YoloV9: Coordinated for its "state-of- the-art detection" abilities, YOLOv9 gives uncommon accuracy in spotting brain tumor abnormalities with few bogus up-sides, so ensuring steady outcomes for use in centers. The table 1 illustrate the performance evaluation table for classification and table 2 shows Performance Evaluation Table for Detection.

4 PERFORMANCE METRICS

Accuracy.

$$\text{Accuracy} = \frac{T_p+T_N}{T_p+F_N+T_N+F_N} \quad (1)$$

Precision.

$$\text{Precision} = \frac{\text{True}_{\text{positive}}}{\text{True}_{\text{positive}} + \text{True}_{\text{Negative}}} \quad (2)$$

Recall.

$$\text{Recall} = \frac{T_p}{T_p+F_N} \quad (3)$$

F1-Score.

$$\text{F1 Score} = 2 * \frac{\text{Recall X Precision}}{\text{Recall+Precision}} * 100(1) \quad (4)$$

MAP.

$$"mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k" \quad (5)$$

Where,
MAP- mean average precision
AP- the “average precision
K-over all clients or searches

For Classification.

Table 1: Performance evaluation table for classification.

Model	Accuracy	Precision	Recall	F1-Score
EfficientNetB2	89.7	89.7	89.7	89.7
ResNet152	77.5	82.3	74.2	76.9
DCNN	81.1	55.0	93.1	67.9
Exception	85.4	86.9	83.0	84.3
NASNetMobile	92.9	93.1	93.0	93.0

For Detection:

Table 2: Performance evaluation table for detection.

Model	Precision	Recall	mAP
YOLOV5s6	86.3	79.3	86.9
YOLOV5x6	73.3	60.7	81.7
YOLOV8	73.2	80.5	86.7
YOLOV9	84.3	78.9	78.6

5 RESULTS

The figure 2 shows Uploading an Input Image for Detection and figure 3 shows Final Outcome. The figure 4 and 5 illustrate Uploading an Input Image for Classification and Final outcome.

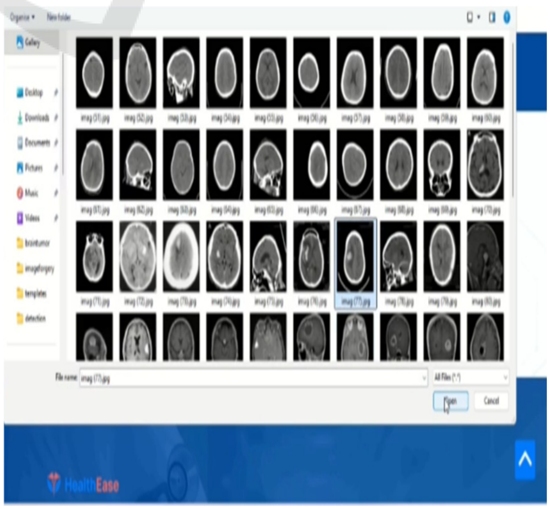

Figure 2: Uploading an input image for detection.

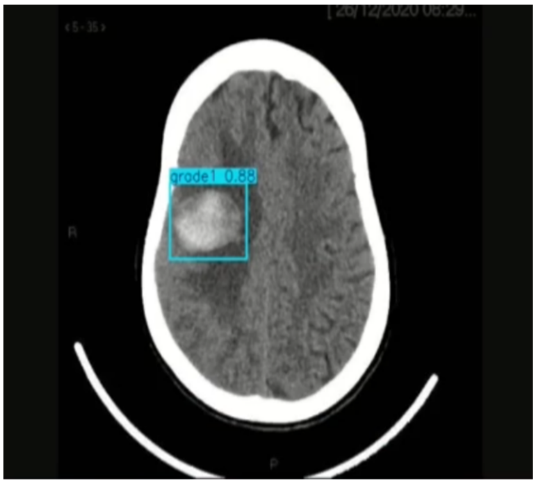

Figure 3: Final outcome.

Figure 4: Uploading an input image for classification.

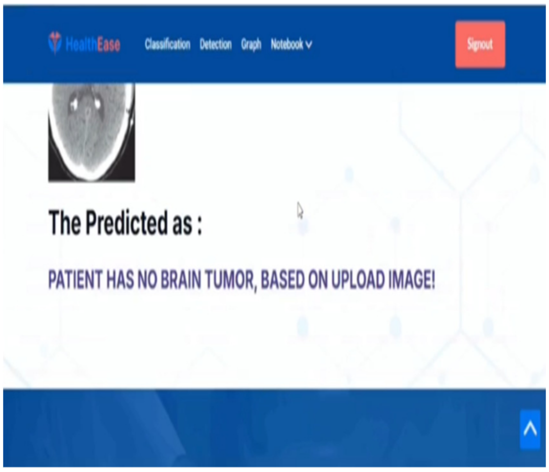

Figure 5: Final outcome.

6 CONCLUSIONS

The suggested approach for brain tumor differential verification and programming demonstrates a notable increase in accuracy and reliability by utilizing state-of-the-art machine learning and deep learning techniques. Through the integration of "deep convolutional neural networks (DCNNs)" with cutting-edge transfer learning models, the approach successfully divides mental diseases into four different grades: "Grade 0 (no tumor), Grade I (little tumor), Grade II (medium-sized tumor), and Grade III (big tumor)." Although the combination model of "Exception and NasNetMobile" achieves exceptional performance with "accuracy of 98.1%, precision of 98.3%, recall of 97.9%, and F1 score of 98.1%," the DCNN and ResNet152 mixing model provides a respectable standard for cancer order. With a recall of 78.9%, precision of 84.3%, and mean average precision (mAP) of 78.9%, These discoveries show how definitively the framework recognizes and arranges cancers, which makes it a significant instrument for clinical navigation. The intuitive point of interaction in light of Flask ensures safe confirmation and effortlessness of purpose, in this manner overcoming any issues among innovation and helpful medical services applications. Extending the dataset to integrate a more shifted range of tumour sorts and imaging settings will assist with working on model speculation and hence the future degree of this brain tumour detection and grouping technique. Clinically, coordination with ongoing MRI or CT scan information for live tumour identification and classification could further develop handiness. Counting "explainable artificial intelligence (XAI)" approaches would likewise assist with expanding process transparency for deciding. Further refining of the YOLO demonstrates for quicker and more exact distinguishing proof could additionally work on continuous relevance in clinical circumstances.

Data set link: https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset/data.

REFERENCES

A novel method for detecting and identifying brain tumors using transfer learning. Applied Sciences, Issue:12(Volume :11), Pg-5645. Ullah, Nissar., Khan, Junaid. Aamjad., Khan, Mohammed. Siraj., Khan, Walleha., Hassan, Ismail., Obayya, Mourice., Salama, Alka. Sharma., 2022.

A comprehensive review of machine learning, hybrid deep learning, and transfer learning techniques for Magnetic

Resonance Imaginging- based classification & segmentation in brain tumor analysis. Multi-media Tools & Appls, Pg-1-38. Das, Sumit., & Goswami, Rahul. Sandesh. ,2024.

An advanced Brain tumor Detection and Classification system in medical image processing utilizing a hybrid deep CNN-Cov-19-Res-Net Transfer learning model. Biomedical Signal Processing and Control, Kumar, Kiran. Arun., Prasad, Aja. Y., & Metan, Jonnes.,2022.

An efficient hybrid transfer learning model for medical diagnosis of brain tumors within a classification framework. Diagnostics, Issue 12(Volume 10), pg 2541. Samee, Niakath. Abrar., Mahmoud, Nouman. Fatehi., Atteia, Golab., Abdallah, Haleed. Amir., Alabdulhafith, Mohsi., Al-Gaashani, Moin. Sheikh., & Muthanna, Multan. Sialkot. Abbatabad.,2022.

CNN transfer learning approach for automated brain tumor detection. Medical and Biological Engineering and Computing, Issue 61(volume 7), Pg-1821-1836. Bairagi, Viraha. Kumar., Gumaste, Pratima., Rajput, Solace. Hulka., & Chethan, Ketan. S.,2023.

Employing deep learning convolutional neural network with transfer learning for brain tumor detection. Internl. Journ. of Imaging Systems & Tech., Anjum, Sahay., Hussain, Lukkal., Ali, Meer., Monagi H. Alkinani., & Duong, T. Quresihsi.,2022.

Enhancing the efficacy of various deep transfer learning-based models in brain tumor detection from MR images. IEEE Access, Volume 10, Pg34716-34730. Asif, Suraigha., Yi, Wien., Ain, Quaan. Ushu., Hou, Jin., Yi, Tia., & Si, Juan.,2022.

Enhancing brain tumor classification using a combination of CNN & transfer learning. Knowledge-Based Systems, 111981. İncir, R., & Bozkurt, F.,2024.

Evaluating deep transfer learning approaches for brain tumor classification performance using MRI images. Journ.of Healthcare Engg., Issue 2022(Volume 1), Pg-3264367. Srinivas, Chinna., Kumar Singh, Nutan . Parashar., Zakariah, Mushir., Porashar Alothaibi, Yall.Aali., Shaukat, Khaled., Partibane, Bhilal., & Awal, Hulaik.,2022.

Hybrid - NET: Combining DenseNet169 and advanced machine learning classifiers for improved brain tumor diagnosis. Internl. Journ. of Imaging Sys. & Tech., Khan, Sohail. Ushu . Rixckie., Zhao, Muah., Asif, Sheikh., & Chen, Xian.,2024.

Image-based brain tumor detection and comparison of transfer learning methods with 3-layer Convolutional Neural Network. Khaliki, M. Z., & Muhammet Sinan Başarslan.,2024.

Improving brain tumor classification through an extensive analysis of transfer learning techniques & model efficiency using Magnetic Resinance Imaging datasets. Shamshad, Numaid., Sarwr, Delloitte., Almogren, Archin., Saleem Khan, Khaled., Munawar, Ali., Rehman, Aamir. Umar., & Bharany, Shahid. ,2024.

Utilizing hybrid deep learning models for brain tumor detection and classification. Scientific Reports, Volume13(Issue - 1), Pg-23029. Babu Vimala, Balak., Srinivasan, Shohesh., Mathivanan, Sisir. Kumar., Mahalakshmi, Jayagopal, Prakash., & Dalu, Gopal. Timor. ,2023.

Utilizing advanced machine learning techniques and knowledge transfer for precise brain tumor identification. Mathivanan, S. Kumar., Sonaimuthu, Srinivasa., Murugesan, Shanmukha., Rajadurai, Hitesh., Shivahare, Bolan. Duleep., & Shah, Mohammaed. Aziz.,2024.