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Deep Learning-Based Brain Tumor Detection and Classification from MRI Images Using CNN and YOLOv8

Meghana D P[1], T Chandraiah[2], Prem Singh M[3], Poornima B H[4], Basavanna M[5], Latharani T R[6]

[1]*Department of Studies in Computer Applications (MCA), Davangere University, Davangere, Karnataka, India.*
[2]*Department of Computer science, Yuvaraja College, University of Mysore, Mysore, Karnataka, India.*
[3]*Department of Computer Science Government College (Autonomous), Mandya, Karnataka, India.*
[4,5]*Department of Studies in Computer Science, Davangere University, Davangere, Karnataka, India.*
[6]*Department of Computer Science and Engineering, Ramiah University of Applied Sciences, Bangalore, Karnataka, India*

***Abstract*— Brain tumour detection from MRI images is an important task because delayed identification can affect further medical evaluation and treatment planning. Manual analysis of MRI scans requires time and experienced medical professionals. This project uses deep learning and image-processing techniques to develop a web-based brain tumour detection and classification system. A CNN model is used to preprocess and classify brain MRI images as Normal or Abnormal, while the YOLOv8 model is used to identify possible tumour regions in MRI scans. The CNN model achieved an accuracy of 89.17% on the test dataset. The system also provides secure login, MRI upload, patient-detail entry, result storage, administrator management, and PDF report generation. The project supports preliminary academic decision-making, but its output must be reviewed by qualified medical professionals.**

***Keywords*—Brain Tumour Detection, MRI Images, Deep Learning, CNN, YOLOv8, Image Classification, Flask, React.**

I. INTRODUCTION

Brain tumours are a serious health concern, and early identification is important for further medical evaluation and treatment planning. Magnetic Resonance Imaging (MRI) is commonly used to examine brain tissues because it provides detailed images. However, manual examination of MRI images requires time, experience, and careful review by medical specialists. In hospitals or diagnostic centres with many scans, the review process may become difficult to manage. Basic image-analysis systems may also lack secure user access, patient-record storage, and report-generation facilities.

Deep learning and image processing provide useful support for analysing medical images. This project focuses on brain tumour detection and classification from MRI images using CNN and YOLOv8 models. The CNN model is used to classify MRI images as Normal or Abnormal, while the YOLOv8 model is used to detect possible tumour regions in the scan. The uploaded MRI image is validated, preprocessed, and analysed through the developed web application.

The system is developed using a React frontend and Flask backend. Doctors can log in, enter patient details, upload MRI images, view prediction results, and download PDF reports. The application stores prediction records in an SQLite database and provides administrator functions for user and report management. This makes the workflow more organised and supports preliminary analysis of MRI images.

A. Problem Statement

Brain tumours can affect patient health, and MRI-image analysis requires careful examination by experienced medical professionals. Manual analysis may be time-consuming, especially when a large number of scans must be reviewed. Basic systems may not provide both MRI classification and possible tumour-region detection with secure record management.

An automated system using image processing and deep learning can support preliminary MRI analysis. This project uses a CNN model to classify MRI images as Normal or Abnormal and YOLOv8 to detect possible tumour regions.

B. Objectives

1. To develop a secure web-based system for brain MRI image upload, classification, and tumour detection using deep learning.
2. To preprocess uploaded MRI images, classify them as Normal or Abnormal using a TensorFlow/Keras CNN model, and detect possible tumour regions using YOLOv8.
3. To store patient details, classification results, detection details, confidence scores, and timestamps in an SQLite database.
4. To provide role-based access, administrator management, and downloadable PDF report generation.

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C. Sample Images

In this paper, brain MRI sample images were collected from publicly available datasets to analyse normal and abnormal brain conditions using deep learning. The dataset includes MRI images representing **Normal** and **Abnormal** classes.

The MRI images contain different brain tissue patterns and possible tumour appearances.

The images are validated and preprocessed using RGB conversion, resizing, normalisation, and basic image-quality checks before analysis. The CNN model classifies each MRI image as Normal or Abnormal, while YOLOv8 detects possible tumour regions and marks them using bounding boxes.

The final output displays the classification result and detection information for preliminary academic decision support.

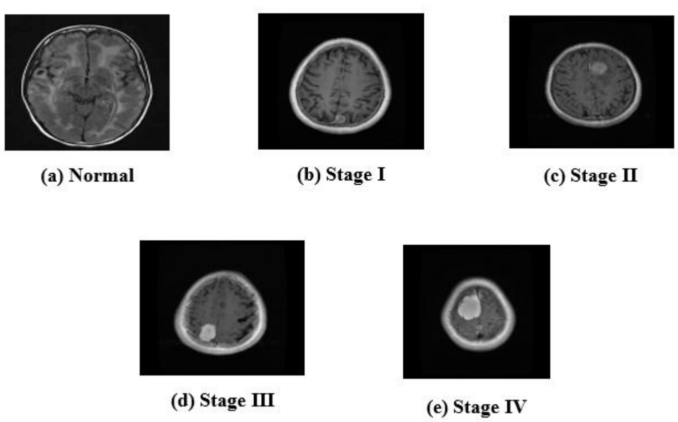

Fig 1. Sample MRI Images

For this paper, a dataset of brain MRI images containing Normal and Abnormal cases was used for model training and testing. The images were collected from publicly available MRI datasets and organised into separate training and testing folders. The dataset includes MRI scans with different tissue appearances and possible tumour patterns to support binary classification. All images were preprocessed using validation, RGB conversion, resizing to 150 × 150 pixels, pixel normalisation, and image-quality checks before being provided to the CNN model. YOLOv8 was additionally used to detect possible tumour regions in MRI images.

The rest of this paper is organised as follows: Section II presents the literature survey and existing research methods. Section III explains the proposed methodology and system design. Section IV discusses the experimental results and analysis. Section V presents the conclusion and future work, followed by the references.

II. Related Work

1. Zahoor et al. (2024) proposed Res-BRNet, a residual and regional CNN model for brain MRI classification. The model used regional and boundary features, but it relied on public datasets for evaluation.
2. Benzorgat et al. (2024) combined DenseNet201, InceptionV3, InceptionResNetV2, and transformer attention for brain-tumour classification. The approach achieved strong results, but it requires high computational resources.
3. Alshuhail et al. (2024) developed a CNN-based MRI classification method with Grad-CAM visualisation. The study improved interpretability, but variation in MRI quality can affect performance.
4. Aamir et al. (2025) developed an automated framework using image enhancement, segmentation, attention-based feature extraction, and ensemble classification. The model reported high performance, but the workflow is computationally intensive.
5. Nimmagadda and Devi (2025) applied YOLOv7 for brain-tumour detection and classification from MRI images. The system detects tumour locations, but requires bounding-box-labelled data.
6. Ali et al. (2025) combined MRI segmentation, hybrid feature extraction, deep learning, and machine learning for multiclass tumour classification. The approach showed strong performance, but depends on dataset optimisation.
7. Srinivas and Parvathi (2026) proposed an explainable CNN model for brain MRI classification. The system used Grad-CAM, LIME, and feature maps to explain predictions, but further clinical testing is required.
8. Vasanthi et al. (2026) developed a federated multimodal deep-learning framework for brain-tumour classification. The model supports privacy-preserving training without sharing raw hospital data, but communication cost remains a challenge.

III. Methodology

The proposed methodology involves collecting and organising brain MRI images into Normal and Abnormal categories for training and testing. The MRI images are preprocessed through image validation, RGB conversion, resizing, normalisation, and quality checking to prepare suitable input for deep-learning models.

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A Convolutional Neural Network (CNN) is trained and used to classify MRI images as Normal or Abnormal. In addition, the YOLOv8 model is used to detect possible tumour regions and highlight them using bounding boxes. Finally, the system is evaluated using performance measures such as accuracy, precision, recall, and F1-score, while YOLOv8 detection performance can be measured using confidence values and mAP.

1. Requirement Analysis

The first phase focuses on identifying the functional and non-functional requirements of the Medical Report Analyzer. The system is required to allow users to upload medical reports, classify them into appropriate categories, extract important medical information, generate summaries, provide health advice, and securely store the resultSystem requirements such as login, doctor/admin roles, MRI upload, prediction, record storage, PDF reports, security, and image validation were identified.

2. System Design

The design includes the React frontend, Flask backend, TensorFlow/Keras model, SQLite database, JWT authentication, APIs, and prediction flow.

3. Implementation (Coding)

React was used for the interface, while Flask and Python handle authentication, image validation, prediction, database operations, and PDF reports.

4. Integration and Testing

The frontend, backend, model, and database were integrated and tested for login, MRI upload, prediction, record storage, and report generation.

5. Deployment

The system runs locally for academic demonstration. Doctors access predictions, while administrators manage users and reports.

6. Maintenance

The system can be improved through bug fixes, security updates, model updates, larger datasets, and cloud deployment.

A. Architecture Diagram

The system architecture consists of a React frontend, Flask backend, TensorFlow/Keras deep-learning model, SQLite database, and PDF-report module. Doctors can log in, enter patient details, upload brain MRI images, view Normal or Abnormal predictions, and download reports.

Administrators can manage users, monitor prediction records, and view system statistics. The Flask backend handles authentication, image validation, preprocessing, prediction, database operations, and report generation. The SQLite database stores user, patient, and prediction details.

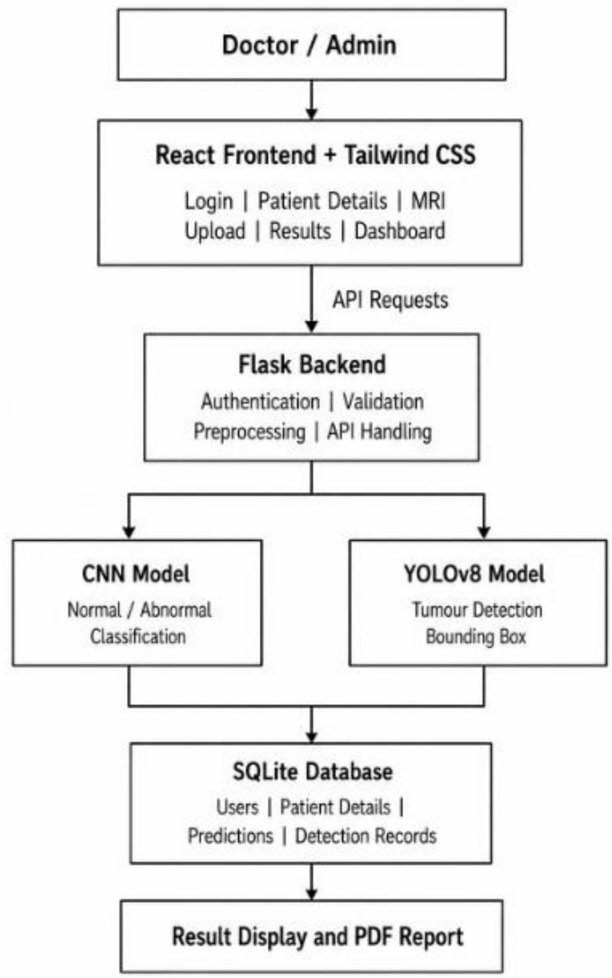

Fig.2 System Architecture

1) Workflow Explanation

The system workflow begins when a doctor or administrator accesses the React-based web application and logs in securely. The doctor enters patient details and uploads a brain MRI image. The Flask backend validates the image and performs preprocessing, including RGB conversion, resizing, and normalisation. The preprocessed image is analysed by the CNN model to classify it as Normal or Abnormal, while the YOLOv8 model identifies possible tumour regions using bounding boxes and confidence scores.

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The final result is displayed through the frontend and stored in the SQLite database with patient and prediction details. Doctors can download a PDF report, and administrators can manage user accounts and monitor prediction records.

2) Algorithm: CNN for Brain Tumor Classification

Input: Brain MRI image

Output: Normal or Abnormal classification with confidence score

1. Load the trained CNN model.
2. Read and validate the uploaded MRI image.
3. Convert the image to RGB format and resize it to (150 times 150) pixels.
4. Normalize pixel values:

$$I_{norm} = \frac{I}{255}$$

5. Add a batch dimension before model prediction:

$$X = \mathrm{expand\_dims}(I_{norm}, 0)$$

6. Apply convolution to extract image features:

$$F(i,j) = \sum_m \sum_n I\,(i+m, j+n) \times K(m,n)$$

Where \(I\) is the input image and \(K\) is the convolution filter.

7. Apply ReLU activation:

$$\mathrm{ReLU}(x) = \max(0, x)$$

8. Apply max-pooling to reduce feature-map size:

$$P(i,j) = \max_{m,n} F(i+m, j+n)$$

9. Pass extracted features through the fully connected layer:

$$Z = W \cdot X + b$$

10. Calculate class probabilities using Softmax:

$$P(y = i|X) = \frac{e^{z_i}}{\sum_{j=1}^{C} e^{z_j}}$$

Where \(C = 2\) represents the Normal and Abnormal classes.

11. Select the class with the highest probability:

$$\hat{y} = \arg\max(P(y = i|X))$$

Display the predicted class and confidence score.

3) Algorithm: YOLOv8 for Brain Tumor Detection

Input: Brain MRI image

Output: Possible tumour region with bounding box, class label, and confidence score

1. Load the trained YOLOv8 model.
2. Read and validate the uploaded brain MRI image.
3. Resize and normalise the image to the YOLOv8 input size:

$$I_{norm} = \frac{I}{255}$$

4. Pass the image through the **backbone** network to extract important features:

$$F = \mathrm{Backbone}(I_{norm})$$

5. Use the **neck** network to combine features at multiple scales:

$$F_{multi} = \mathrm{Neck}(F)$$

6. Use the detection head to predict the bounding box, class score, and object confidence:

$$B = (x, y, w, h)$$

7. Calculate the confidence score:

$$\mathrm{Confidence} = P(\mathrm{Object}) \times P(\mathrm{Class}|\mathrm{Object})$$

8. Calculate Intersection over Union (IoU) for overlapping bounding boxes:

$$\mathrm{IoU} = \frac{\mathrm{Area}(B_{pred} \cap B_{true})}{\mathrm{Area}(B_{pred} \cup B_{true})}$$

9. Apply Non-Maximum Suppression (NMS) to remove duplicate boxes:

$$B_{final} = \mathrm{NMS}(B, \mathrm{IoU}_{threshold})$$

10. Display the final output with the possible tumour bounding box, predicted label, and confidence score.

IV. Technology Used

React: Used to develop the frontend interface for login, MRI upload, result display, and dashboard pages.

Python and Flask: Used to build the backend APIs for authentication, image processing, prediction, database operations, and report generation.

TensorFlow and Keras: Used to run the CNN model for classifying brain MRI images as Normal or Abnormal.

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YOLOv8: Used to detect possible tumour regions in MRI images using bounding boxes and confidence scores.

SQLite: Used to store user details, patient information, and prediction records.

A) Libraries Used

TensorFlow and Keras: Used to load and run the CNN model for classifying brain MRI images as Normal or Abnormal.

Ultralytics YOLOv8: Used to load and run the YOLOv8 model for detecting possible tumour regions and generating bounding boxes.

NumPy: Used to convert MRI images into numerical arrays and normalise pixel values.

Pillow (PIL): Used to open, validate, convert, and resize uploaded MRI image files.

OpenCV: Used for image validation, image processing, and basic MRI-image analysis.

Flask: Used to create backend API routes and handle server-side application logic.

Flask-CORS: Used to allow communication between the React frontend and Flask backend.

Flask-SQLAlchemy: Used to create and manage SQLite database tables for users, patients, and predictions.

Flask-Bcrypt: Used to hash passwords securely and verify them during login.

Flask-JWT-Extended: Used to implement JWT authentication and role-based access control.

ReportLab: Used to generate downloadable PDF prediction reports.

Python-dotenv: Used to load environment variables and configuration settings securely.

V. RESULTS

The proposed system successfully analysed brain MRI images through a web-based application. The CNN model classified MRI images as Normal or Abnormal and achieved 89.17% accuracy, 92.01% precision, 87.42% recall, and 88.46% F1-score on 711 test images. YOLOv8 detected possible tumour regions and displayed bounding boxes with confidence scores. The application also supported secure login, MRI upload, patient-detail entry, prediction storage, administrator functions, and PDF report generation. These results show that the system can support preliminary MRI-image analysis; however, all outputs require review by qualified medical professionals.

The YOLOv8 model was trained for 50 epochs to detect possible brain tumour regions in MRI images. The final model achieved 97.83% precision, 97.92% recall, 98.75% mAP@0.5, and 76.55% mAP@0.5:0.95. The model produces bounding boxes around possible tumour regions along with confidence scores. These results indicate strong detection performance on the project dataset; however, the output is intended for academic decision support and requires expert medical review.

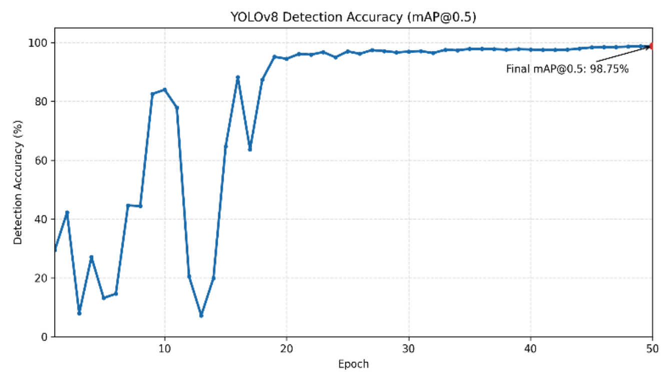

Fig.3 YOLOv8 Detection Accuracy Graph

Table I Comparison Table between CNN and Yolov8 Based on the Accuracy and Loss Values

Models	Accuracy (%)	Loss Value
CNN	89.17	10.83
YOLOv8	98.75	1.25

Table II Reported Performance of Existing Deep Learning Methods and the Proposed System

Method	Task	Dataset / Benchmark	Reported Result
Res-BRNet [1]	Image Classification	Figshare + Kaggle	98.22% Accuracy
CNN Ensemble + Transformer [2]	Image Classification	Cheng	99.34% Accuracy
CNN Ensemble + Transformer [2]	Image Classification	BT-large-2c	99.16% Accuracy
CNN Ensemble + Transformer [2]	Image Classification	BT-large-4c	98.62% Accuracy
CNN-based Method [3]	Image Classification	Brain MRI Dataset	98.00% Accuracy
YOLOv7 [4]	Tumor Detection	Roboflow Brain MRI Dataset	87.9% mAP@0.5
VGG16 + Fine-Tuning [5]	Image Classification	Public Brain MRI Datasets	99.24% Accuracy
Proposed CNN	**Image Classification**	**Proposed Brain MRI Dataset**	**89.17% Accuracy**
Proposed YOLOv8	**Tumor Detection**	**Proposed Brain MRI Dataset**	**98.75% mAP@0.5**

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1) Snapshots:

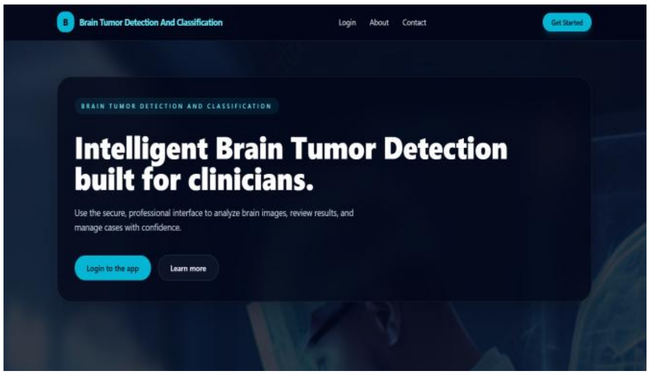

Fig 4. Home Page

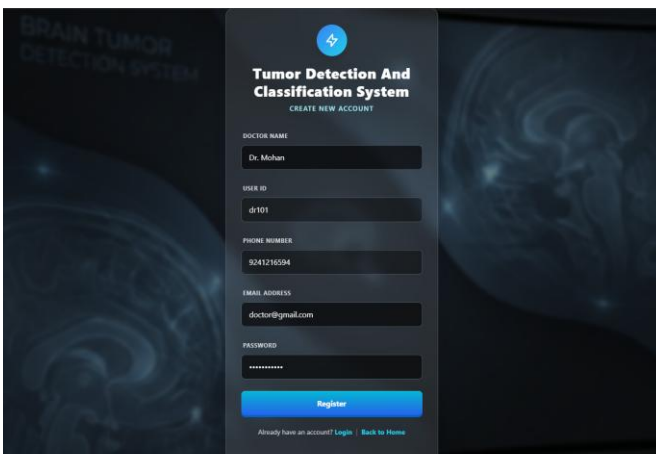

Fig 5. Doctor Registration Page

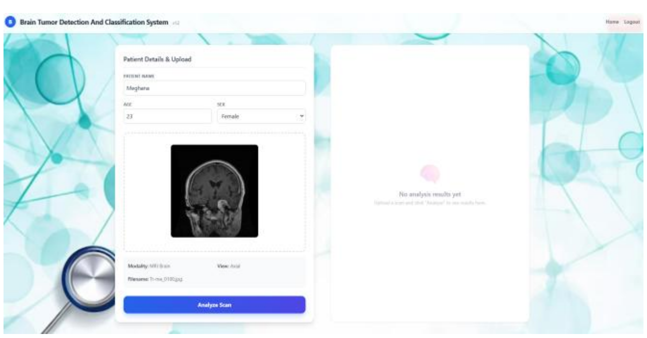

Fig 6. Brain MRI Classification Result

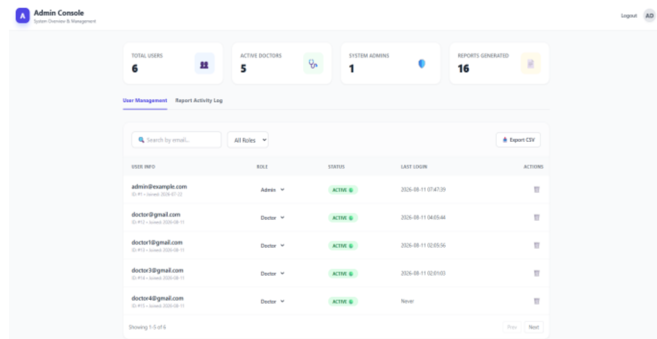

Fig 7. Administrator Dashboard

The process begins when the doctor logs in to the system using valid credentials. After successful authentication, the doctor enters patient details and uploads a brain MRI image. The system validates and preprocesses the image before sending it to the CNN and YOLOv8 models. The CNN classifies the MRI image as Normal or Abnormal, while YOLOv8 detects possible tumour regions with bounding boxes and confidence scores. Finally, the prediction result is displayed, stored in the database, and can be downloaded as a PDF report.

VI. Conclusion

This paper presented a web-based Brain Tumor Detection and Classification system using deep learning and brain MRI images. The system combines two models to support MRI analysis. The CNN model classifies the uploaded MRI image as Normal or Abnormal, while the YOLOv8 model detects possible tumour regions and displays them using bounding boxes and confidence scores. This combined approach provides both an overall classification result and a visual indication of suspected tumour locations.

The developed application includes secure user login, patient-detail entry, MRI-image upload, image validation, preprocessing, result display, prediction-record storage, administrator functions, and PDF report generation. The CNN model achieved 89.17% classification accuracy on the test dataset. The YOLOv8 model achieved 98.75% mAP@0.5 for tumour-region detection. The project demonstrates that React, Flask, TensorFlow/Keras, YOLOv8, and SQLite can be integrated into a complete medical-image analysis workflow.

The system is developed as an academic decision-support prototype. Its results can support preliminary review of MRI images, reduce manual effort, and improve the organisation of prediction records. However, the system does not replace radiologist interpretation, clinical diagnosis, or treatment planning. All model outputs must be reviewed by qualified medical professionals before making any medical decision.

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