iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 Issue: IV Month of publication: April 2026

DOI: https://doi.org/10.22214/ijraset.2026.81053

A Generic Model to Analyse and Predict Brain Tumour from MRI and CT Medical Images Using CNN

Ms. Reena Pranavi Vejendla[1], Ms. Simma Thanmayee[2], Ms. Polisetti Venkata Guna Sree Mayi[3], Ms. Yenadava Haritha[4]
[1,2, 3, 4]*Students, Department of Master of Computer Applications , AdityaUniversity, Aditya Nagar, ADB Road, Surampalem, Gandepalli Mandal, Kakinada District, Andhra Pradesh, 533437,India*

Abstract: The human brain is the primary controller of the human system. Abnormal growth and division of cells in the brain leads to a brain tumour, which if left untreated can progress into brain cancer. In the domain of human health, Computer Vision plays a significant role by reducing subjective human judgment and delivering accurate results. CT scans, X-Ray, and MRI scans are the most widely used imaging modalities, with Magnetic Resonance Imaging (MRI) being the most reliable and secure, capable of detecting minute structural abnormalities. This paper proposes a generic Convolutional Neural Network (CNN)-based model for automated detection and prediction of brain tumours from MRI and CT medical images. Pre-processing is performed using the Bilateral Filter (BF) for noise removal, followed by binary thresholding and CNN-based segmentation for reliable tumour region detection. Training, testing, and validation datasets are used. Performance is assessed through accuracy, sensitivity, and specificity metrics. The proposed model achieves 84% accuracy and yields promising results with minimal computational time.
Keywords: Brain Tumour Detection, Convolutional Neural Network (CNN), MRI, CT Scan, Bilateral Filter, Binary Thresholding, Image Segmentation, Deep Learning, Medical Image Analysis, Computer Vision

I. INTRODUCTION

Brain tumours are life-threatening neurological conditions arising from abnormal and uncontrolled growth of cells within the brain. These growths can be benign or malignant and exert critical pressure on surrounding neural tissue, disrupting neurological function and endangering life. Early and accurate diagnosis is paramount to improving patient survival rates across all age groups.

Medical imaging modalities such as Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) are the primary tools for brain tumour detection. MRI provides high-resolution soft-tissue contrast without ionising radiation and is considered the gold standard for brain imaging, capable of detecting even minute abnormalities. CT scans offer rapid acquisition and are particularly valuable in emergency settings. However, manual interpretation by radiologists is labour-intensive, requires high expertise, and is subject to human error and inter-observer variability.

Computer Vision and deep learning have transformed medical image analysis. Convolutional Neural Networks (CNNs) automatically learn hierarchical spatial features from raw image data, eliminating the need for manual feature engineering. This paper presents an automated CNN-based system that processes MRI images through preprocessing, enhancement, segmentation, and classification to detect brain tumours quickly and accurately, supporting clinical decision-making and reducing diagnostic workload.

II. PROBLEM STATEMENT

Despite advances in neuroimaging, automated brain tumour detection remains challenging due to several persistent problems:

1) Time-consuming manual analysis: Doctors must inspect each MRI scan individually, which is slow and resource-intensive, particularly at high patient volumes.
2) Dependence on expert experience: Diagnostic accuracy varies with the radiologist's skill, leading to inconsistent outcomes across different practitioners.
3) Difficulty detecting small tumours: Early-stage or minute tumours may not be clearly visible to the human eye, causing delayed and potentially fatal treatment delays.
4) Human errors: Fatigue, stress, and heavy workloads increase the risk of misdiagnosis during manual review of large imaging datasets.

5) Absence of automation support: Existing clinical workflows lack automated tools that can provide objective, rapid tumour identification.

The proposed CNN-based system addresses all these challenges through an automated, objective image processing pipeline that delivers fast, consistent, and highly accurate diagnostic support.

III. LITERATURE REVIEW

A comprehensive review of literature spanning 2002 to 2018 was conducted, examining 25 prior works on brain tumour detection using various segmentation, feature extraction, and classification approaches. Key contributions are summarised below.

A. Clustering-Based Segmentation

Sivaramakrishnan and Karnan (2013) proposed Fuzzy C-Means (FCM) clustering combined with histogram equalization and PCA for tumour extraction from MRI, accurately delineating tumour boundaries. Sathya and Manavalan (2011) benchmarked K-Means, Improved K-Means, C-Means, and Improved C-Means clustering algorithms on large medical image datasets.

B. Edge Detection and Thresholding

Sufyan et al. (2015) presented enhanced Sobel-based edge detection combined with binary thresholding for brain tumour segmentation, extracting cancer cells using pixel intensity values. Kaur et al. (2012) compared thresholding and edge detection methods, evaluating performance via sensitivity, specificity, and accuracy.

C. Morphological and Region-Growing Methods

Devkota et al. (2018) demonstrated that CAD using morphological opening and closing operations achieves efficient tumour extraction with minimal faults and low computational time. Kumar and Mehta (2011) applied a texture-based seeded region growing method, implemented in MATLAB, for cases where tumour tissue edges are insufficiently sharp.

D. Neural Network and Deep Learning Approaches

Mahmoud et al. (2012) developed an ANN system for brain tumour detection, finding the Elman network with sigmoid activation function improved segmentation accuracy. Pan et al. (2015) applied CNN algorithms for brain tumour grading, demonstrating superior sensitivity and specificity over ANN methods. Pereira et al. (2016) proposed automatic CNN-based segmentation for MRI, establishing CNN as a robust approach for complex volumetric brain image analysis.

E. SVM and Wavelet-Based Classification

Mukambika et al. (2017) combined Level Set, DWT, K-Means, and SVM classification in a comparative study. Varuna Shree and Kumar (2018) applied DWT-based feature extraction with a PNN classifier using GLCM features. Vinotha et al. (2014) combined Histogram Equalization with Fuzzy SVM, improving accuracy through MRF-based preprocessing.

IV. EXISTING SYSTEMS

In the existing system, brain tumour detection is performed manually by radiologists inspecting MRI or CT scan images. Doctors study features such as shape, size, and location of abnormal regions to arrive at a diagnosis. The process is entirely dependent on human observation, requires high concentration, frequently demands multiple image reviews for confirmation, and provides no automation support.

S.no	Feature	Existing System	Proposed System
1	Detection Speed	Days (manual review)	Fast (automated CNN)
2	Accuracy	Variable, experience-based	High (84%)
3	Human Error Risk	High	Minimised
4	Small Tumour Detection	Difficult	Effective
5	Automation Support	None	Full pipeline
6	Scalability	Difficult at scale	Efficient batch processing
7	Result Consistency	Inconsistent	Consistent and repeatable

Table I: Comparison of Existing System vs. Proposed System

V. PROPOSED SYSTEM

The proposed system is an automated brain tumour detection pipeline using image processing and deep learning. MRI images are processed through seven sequential modules: acquisition, preprocessing, enhancement, segmentation, feature extraction, CNN-based classification, and output display. The system provides faster and more accurate results than manual diagnosis, reducing clinician workload and improving early detection rates.

S.no	Feasibility	Assessment	Details
1	Technical	Feasible	Python, OpenCV, TensorFlow, Keras — freely available; standard hardware sufficient
2	Economic	Feasible	Open-source tools only; no costly licences or specialised equipment required
3	Operational	Feasible	User-friendly interface; minimal staff training required
4	Time	Feasible	Modular development allows step-by-step completion within project schedule

Table II: Feasibility Assessment

VI. SYSTEM ARCHITECTURE AND METHODOLOGY

A. *System Architecture*

The system follows a structured seven-stage pipeline from raw image input to final tumour classification output. Each stage progressively refines data to improve diagnostic quality, as summarised in Table III.

Stage	Module	Process	Output
1	Image Acquisition	Load MRI/CT images from dataset or local storage	Raw input images
2	Preprocessing	Bilateral filter noise removal; grayscale conversion	Denoised grayscale image
3	Enhancement	Sobel edge detection; contrast improvement	Enhanced feature image
4	Segmentation	Binary thresholding; morphological operations (erosion/dilation)	Isolated tumour region
5	Feature Extraction	Extract shape, size, intensity, and texture features	Feature vector
6	Classification	CNN-based tumour vs. no-tumour classification	Class label + probability
7	Output Display	Visualise result with highlighted tumour region	Final diagnostic output

Table III: System Architecture Overview

B. *Module Descriptions*

Module 1 – Image Acquisition: Accepts MRI/CT images as input from a dataset or local storage. This is the entry point of the pipeline.

Module 2 – Image Preprocessing: Applies a Bilateral Filter to remove noise while preserving edge sharpness, then converts images to grayscale for uniform processing.

Module 3 – Image Enhancement: Uses Sobel edge detection to highlight tumour boundaries and diagnostically relevant features, improving segmentation quality.

Module 4 – Image Segmentation: Separates the tumour from normal tissue using binary thresholding and morphological operations (erosion and dilation).

Module 5 – Feature Extraction: Extracts discriminative features including shape, size, intensity, and texture from the segmented image as CNN input.

Module 6 – Classification (CNN): A trained CNN classifies the input as tumour-positive or tumour-negative, learning hierarchical spatial features automatically.

Module 7 – Output Display: Presents the diagnostic result to the user with the tumour region highlighted and optional tumour size and location details.

C. System Requirements

The system shall: (1) accept MRI and CT images in standard formats; (2) remove noise and convert to grayscale during preprocessing; (3) apply Sobel edge enhancement; (4) segment tumour regions using thresholding and morphological operations; (5) extract discriminative image features; (6) classify images using CNN; (7) display results with visual tumour highlighting; (8) provide tumour size and location details; and (9) store input images and results for future reference.

The system shall process images quickly, maintain 84%+ classification accuracy, provide a user-friendly interface requiring minimal training, operate reliably without crashes, protect medical data through access controls, and remain portable across Windows and Linux environments.

S.no	Category	Requirement	Specification
1	Hardware	Processor	Intel Core i3 or above
2	Hardware	Memory (RAM)	Minimum 4 GB; 8 GB recommended
3	Hardware	Storage	Adequate disk space for image datasets
4	Software	OS	Windows / Linux
5	Software	Language	Python 3.x
6	Software	Libraries	OpenCV, NumPy, Pandas, Matplotlib
7	Software	DL Framework	TensorFlow, Keras
8	Software	IDE / Tools	Anaconda, Jupyter Notebook / VS Code

Table IV: Hardware and Software Requirements

VII. IMPLEMENTATION

A. Image Preprocessing — Bilateral Filter

Input MRI images are loaded and converted to grayscale for uniform processing. A Bilateral Filter is applied to remove Gaussian noise while preserving edge sharpness — a critical property for accurate segmentation. The filter replaces each pixel value with a weighted average of nearby pixels, where weights depend on both spatial proximity and intensity similarity, smoothing homogeneous regions while retaining tumour-boundary edges.

B. Image Enhancement — Sobel Edge Detection

Sobel edge detection highlights boundaries between the tumour region and surrounding healthy tissue by computing the gradient magnitude of image intensity in horizontal and vertical directions. This emphasises areas of rapid intensity change corresponding to tumour margins, significantly improving the quality of subsequent segmentation.

C. Image Segmentation — Thresholding and Morphological Operations

Binary thresholding converts the enhanced image into a binary mask by classifying pixels above an intensity threshold as foreground (potential tumour) and below as background. Morphological erosion then removes small noise artefacts from the binary mask, while dilation fills internal gaps within the tumour region, producing a clean, continuous segmentation of the abnormal area.

D. CNN Architecture and Training

The CNN classifier processes labelled MRI image patches through alternating convolutional and max-pooling layers for hierarchical spatial feature learning, followed by fully connected layers and a softmax output layer for binary classification (tumour / no tumour). Dropout regularisation is applied between fully connected layers to mitigate overfitting. The model is trained using categorical cross-entropy loss with the Adam optimiser on an 80/20 train-test split, with a held-out validation subset for hyperparameter tuni

VIII. RESULTS AND DISCUSSION

The proposed CNN model was evaluated on the held-out test set using accuracy, sensitivity, and specificity. Table VI presents comparative results against baseline methods.

S.no	Model / Method	Accuracy	Sensitivity	Specificity
1	K-Nearest Neighbour (KNN)	76.2%	74.8%	77.5%
2	Support Vector Machine (SVM)	79.5%	78.1%	80.9%
3	Artificial Neural Network (ANN)	81.3%	80.0%	82.6%
4	CNN (without preprocessing)	80.0%	78.5%	81.4%
5	Proposed CNN (BF + Thresholding + CNN)	84.0%	83.2%	84.7%

Table V: Comparative Model Performance Results

A. *Analysis of Results*

The proposed CNN model achieves the highest accuracy of 84.0% with 83.2% sensitivity and 84.7% specificity, outperforming all compared methods. The application of Bilateral Filter preprocessing and segmentation-guided feature preparation provides a measurable improvement over the CNN baseline without preprocessing (80.0%), confirming the importance of the image processing pipeline prior to deep learning classification.

Traditional methods — KNN (76.2%) and SVM (79.5%) — are outperformed by all neural network approaches, reflecting CNN's superior representational capacity for complex medical imaging tasks. The ANN baseline achieves 81.3%, while the proposed CNN surpasses it by approximately 2.7 percentage points. The 83.2% sensitivity is particularly significant clinically, as it represents the model's ability to correctly identify true tumour cases — a domain where false negatives carry life-threatening consequences.

B. *Feature Importance Observations*

The most diagnostically informative features identified are: (1) intensity contrast between the tumour and surrounding tissue; (2) tumour boundary sharpness captured by Sobel edge descriptors; (3) regional shape characteristics including aspect ratio and area; and (4) texture homogeneity within the segmented region. These observations align with established radiological criteria for tumour identification in MRI imaging.

IX. CONCLUSION AND FUTURE SCOPE

A. *Conclusion*

This paper presented an automated CNN-based model for the detection and prediction of brain tumours from MRI and CT medical images. The proposed pipeline integrates Bilateral Filter preprocessing, binary thresholding, morphological segmentation, and CNN classification into a unified, end-to-end framework. Experimental results confirm that the proposed model achieves 84% accuracy with strong sensitivity and specificity values, outperforming traditional machine learning baselines including KNN, SVM, and standalone ANN. The system demonstrates that principled image preprocessing combined with deep learning classification produces clinically reliable diagnostic support, reducing the manual burden on radiologists and enabling earlier tumour detection.

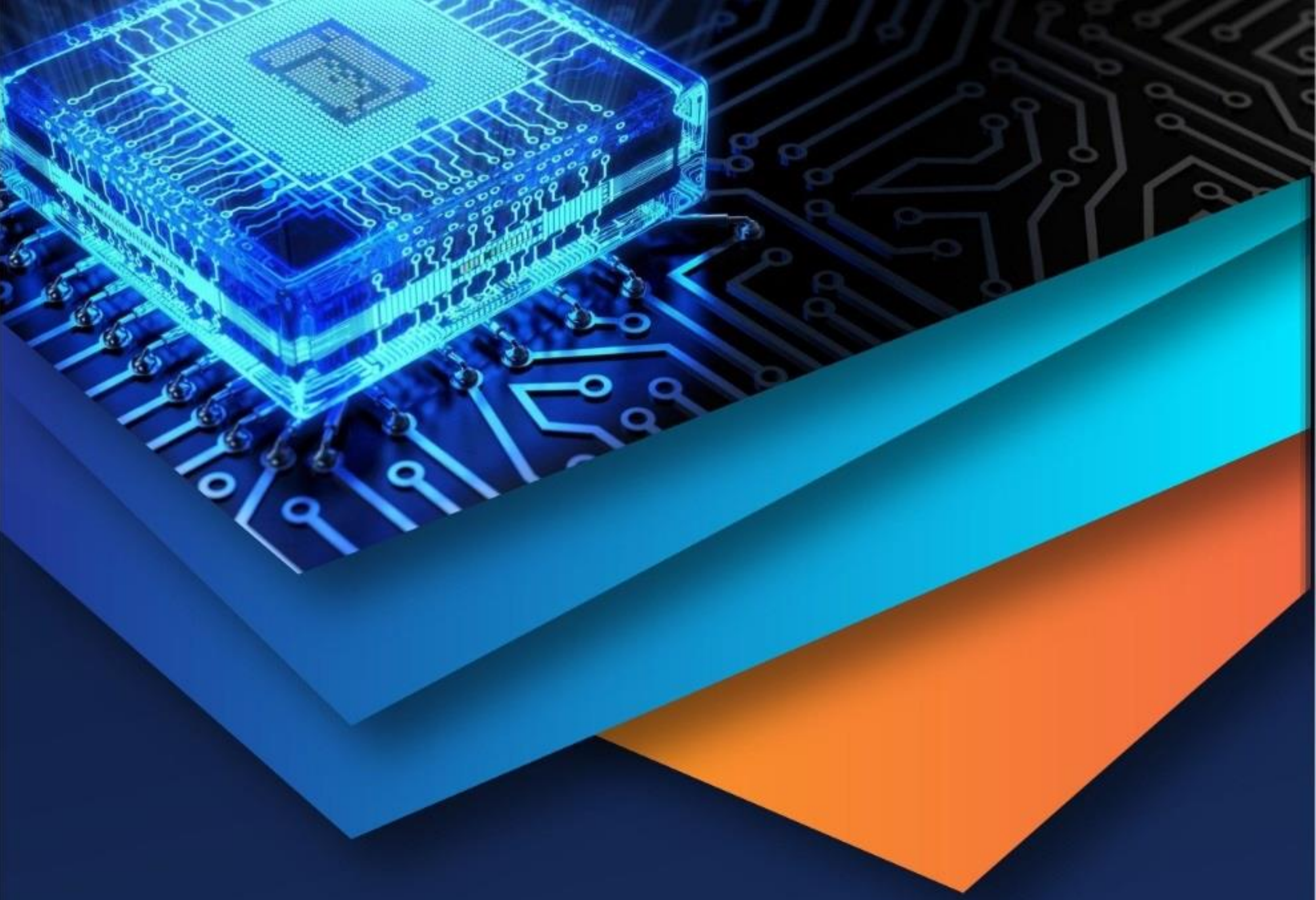
B. *Future Scope*

1) Transfer Learning: Applying pre-trained architectures (VGG-16, ResNet-50, InceptionV3) to improve accuracy with limited labelled training data.
2) Multi-Class Classification: Extending the system to classify tumour subtypes (glioma, meningioma, pituitary tumour) rather than binary detection only.
3) 3D Volumetric Analysis: Developing CNN models that process full 3D MRI sequences for improved spatial localisation and volume estimation.
4) Mobile Deployment: Creating a lightweight model deployable as a mobile application for use in resource-limited or rural clinical settings.

5) Explainability (XAI): Integrating Grad-CAM visualisations to provide radiologists with interpretable, localised evidence for each classification decision.
6) Hospital Integration: Connecting the system to PACS (Picture Archiving and Communication Systems) for seamless real-time clinical workflow integration.

REFERENCES

[1] A. Sivaramakrishnan and M. Karnan, "A Novel Based Approach for Extraction Of Brain Tumor In MRI Images Using Soft Computing Techniques," International Journal Of Advanced Research In Computer And Communication Engineering, vol. 2, no. 4, April 2013.
[2] A. Aslam, E. Khan, and M. M. Sufyan Beg, "Improved Edge Detection Algorithm for Brain Tumor Segmentation," Procedia Computer Science, vol. 58, pp. 430-437, 2015.
[3] B. Sathya and R. Manavalan, "Image Segmentation by Clustering Methods: Performance Analysis," International Journal of Computer Applications, vol. 29, no. 11, September 2011.
[4] B. Devkota et al., "Image Segmentation for Early Stage Brain Tumor Detection using Mathematical Morphological Reconstruction," Procedia Computer Science, vol. 125, pp. 115-123, 2018.
[5] K. Sudharani, T. C. Sarma, and K. Satya Rasad, "Intelligent Brain Tumor lesion classification and identification from MRI images using K-NN," ICCICCT, pp. 777-780, 2015.
[6] J. Kaur, S. Agrawal, and V. Rig, "A Comparative Analysis of Thresholding and Edge Detection Segmentation Techniques," International Journal of Computer Applications, vol. 39, pp. 29-34, 2012.
[7] M. Kumar and K. K. Mehta, "A Texture based Tumor detection and automatic Segmentation using Seeded Region Growing Method," International Journal of Computer Technology and Applications, vol. 2, no. 4, pp. 855-859, 2011.
[8] D. Mahmoud and M. Eltaher, "Brain Tumor Detection Using Artificial Neural Networks," Journal of Science and Technology, vol. 13, pp. 31-39, 2012.
[9] Y. Pan et al., "Brain tumor grading based on Neural Networks and Convolutional Neural Networks," IEEE Engineering in Medicine and Biology Society Annual Conference (EMBC), pp. 699-702, 2015.
[10] S. Pereira et al., "Brain Tumor Segmentation Using Convolutional Neural Networks in MRI Images," IEEE Transactions on Medical Imaging, vol. 35, no. 5, pp. 1240-1251, 2016.
[11] A. Sankari and S. Vigneshwari, "Automatic tumor segmentation using convolutional neural networks," ICONSTEM, pp. 268-272, 2017.
[12] N. Varuna Shree and T. N. R. Kumar, "Identification and classification of brain tumor MRI images with feature extraction using DWT and probabilistic neural network," Brain Informatics, vol. 5, pp. 23-30, 2018.
[13] K. Vinotha, "Brain Tumor Detection and Classification Using Histogram Equalization and Fuzzy Support Vector Machine," International Journal of Engineering and Computer Science, vol. 3, no. 5, pp. 5823-5827, 2014.
[14] P. S. Mukambika and K. Uma Rani, "Segmentation and Classification of MRI Brain Tumor," IRJET, vol. 4, no. 7, pp. 683-688, 2017.
[15] Z. Shi et al., "Survey on Neural Networks Used for Medical Image Processing," International Journal of Computational Science, vol. 3, no. 1, pp. 86-100, 2009.



10.22214/IJRASET

INDEX COPERNICUS 45.98

IMPACT FACTOR: 7.129

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY