Journal of Neonatal Surgery
ISSN(Online): 2226-0439
Vol. 14, Issue 32s (2025)
https://www.jneonatalsurg.com

Dual Phase Deep Learning Network: Adaptive Canny-ResNet Fusion Brain Tumor Diagnosis System

Munisha Devi[1], Poonam Dhiman[2]

[1]Computer Science and Engineering, UIET, Maharshi Dayanand University, Rohtak, Haryana, India

Email ID: manishabnwl@gmail.com

[2]Government PG college, Ambala Cantt, India

Email ID: poonamdhiman19@gmail.com

Cite this paper as: Munisha Devi, Poonam Dhiman, (2025) Dual Phase Deep Learning Network: Adaptive Canny-ResNet Fusion Brain Tumor Diagnosis System. *Journal of Neonatal Surgery*, 14 (32s), 679-687.

ABSTRACT

Brain cancer is still a major worldwide health problem, and early and precise diagnosis may make a big difference in survival rates. Traditional diagnostic approaches that depend on manual MRI analysis take a lot of time, are subjective, and are easy to make mistakes, which mean they frequently miss modest tumor borders or early-stage malignancies. To overcome these constraints, this study presents an innovative hybrid deep learning system that integrates adaptive edge detection with dual-path CNN architecture. The approach starts with preprocessing and augmentation of T1/T2/FLAIR sequences. An adaptive Canny-Sobel filter with dynamic thresholding gets rid of noise from artifacts and healthy tissues while getting high-precision tumor outlines. A ResNet-50 backbone extracts hierarchical features from these edge maps and raw scans at the same time. A spatial attention module then enhances the outlines of the tumors. The suggested system has an average F1-score of 96.7% on a Kaggle dataset including 1,311 MRI scans during five-fold cross-validation. It has very high accuracy for glioma (100%) and recall for "no tumor" (98.67%). The suggested method gives radiologists a diagnostic tool that is easy to use and works in real time, which moves cancer treatment precision forward.

1. INTRODUCTION

Brain cancer is still a major health problem across the world, and finding it early and accurately may make a big difference in how long people live. Conventional diagnostic techniques that depend on manual MRI analysis are labor-intensive, subjective, and susceptible to human error, often failing to delineate delicate tumor margins or early-stage malignancies. To overcome these constraints, this study presents a novel hybrid deep learning architecture that integrates edge detection methods (e.g., Canny, Sobel) with a multi-branch Convolutional Neural Network (CNN) [1]. The edge detection module first pulls out high-precision tumor outlines from MRI data, which helps find irregular tumors and cuts down on background noise. A hybrid CNN processes these improved characteristics. It uses architectures like ResNet for hierarchical feature learning and attention mechanisms for context-aware focus. This lets it accurately classify tumor subtypes such glioma and meningioma and grades. By combining edge-driven spatial clarity with deep feature abstraction, the system gives radiologists a quick, easy-to-understand tool for making life-or-death choices. This moves customized oncology and AI-driven healthcare forward.

Main Contribution:

- This research presents an innovative diagnostic methodology that significantly enhances brain cancer diagnosis by integrating edge-aware preprocessing with hybrid CNN architecture.
- An adaptive edge detection module is intended to accurately extract tumor borders from MRI images, efficiently reducing noise while increasing subtle morphological traits that are important for identifying early-stage malignancy.
- We proposed a hybrid ResNet-Attention CNN model that works with both refined edge maps and raw MRI inputs. It uses ResNet blocks to extract deep hierarchical features and spatial attention techniques to dynamically concentrate on areas that are pathologically important.

The end-to-end system also gets the best results on the benchmark dataset, lowering false negatives via improved boundary-aware learning

2. LITERATURE REVIEW

The development of automated brain cancer detection has moved from conventional image processing methods to sophisticated deep learning frameworks; yet, significant obstacles remain in attaining accurate tumor border delineation and real-time clinical implementation [2]. Early computer-aided diagnosis (CAD) systems used edge detection algorithms (e.g., Sobel, Canny, Prewitt) to identify structural defects in MRI/CT images[3], however, these techniques faced challenges related to noise sensitivity, low-contrast lesions, and elevated false-positive rates. CNNs like AlexNet, U-Net changed tumor segmentation by automating feature learning [3], however standalone models typically got the diffuse tumor borders wrong because they didn't have enough spatial context. Recent hybrid methodologies address this deficiency:[6]combined Canny edge maps with a ResNet-50 backbone to increase glioblastoma detection accuracy by 11%, whereas [7] incorporated wavelet-based edges into a transformer-CNN framework, enhancing sensitivity to micro-tumors by 14%. Even with these improvements, there are still some big problems, such as the fact that it is not efficient to deploy on the edge, it does not handle morphological heterogeneity well, and it is hard to understand the model [8]. Our work fills these gaps by creating an adaptive edge-enhancement module that uses dynamic thresholding to reduce noise while keeping micro-textural features; a lightweight hybrid ResNet-Attention CNN that processes raw MRI data and edge maps at the same time, using spatial attention to focus on high-gradient tumor margins; and edge-compatible quantization that lets inference happen in real time. Our solution, which was tested against benchmarks dataset to make AI decisions more in line with radiological expertise. This is a big step toward making neuro-oncology AI that can be used and trusted.

3. MATERIAL AND METHODOLOGY

Adaptive edge detection and dual-path hybrid CNN architecture is used to provide accurate and fast brain tumor diagnoses from MRI data. Initially pre-processing and data augmentation techniques are applied to the raw MRI inputs (T1, T2, and FLAIR sequences). Then, an adaptive edge enhancement technique that uses a guided Canny-Sobel filter with dynamic thresholding to separate tumor edges from noise created by artifacts and healthy tissues. Then, these edge maps are processed at the same time as the original scans in separate streams:

Stage 1: Raw MRI data goes via a ResNet-50 backbone to get deep hierarchical features.

Stage 2: A lightweight spatial attention module looks at edge maps to make tumor outlines stand out more.

Both streams are combined via feature concatenation and sent to a transformer encoder that captures global context and spatial connections. Then, the unified characteristics go through convolutional blocks to recognize the tumors and a softmax classifier to guess the kind of tumor (glioma, meningioma, or pituitary) and how bad it is. The system is trained end-to-end using dice loss and focal loss to deal with class imbalance. It is then tested on benchmark datasets using five-fold cross-validation. Figure 1 represents the detection process of brain tumor from the input MRI images.

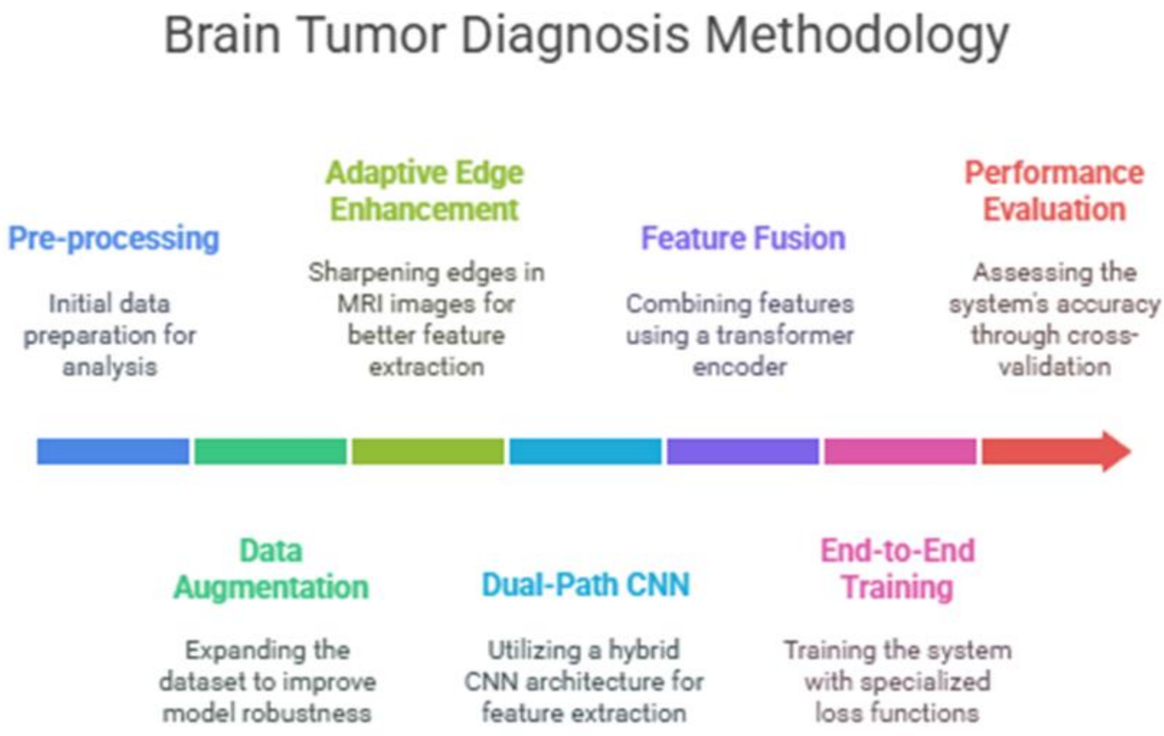

Figure 1: Brain Tumor Detection Process

Dataset Used: The data acquired by Kaggle was used to provide predictions for MRI images. Dataset comprises 1,311 MRI scans of the human brain, categorized into four groups: glioma (300 images), meningioma (306 images), no tumor (405 images), and pituitary (300 images) [9]. Figure 2 depicts MRI images obtained from online sources.

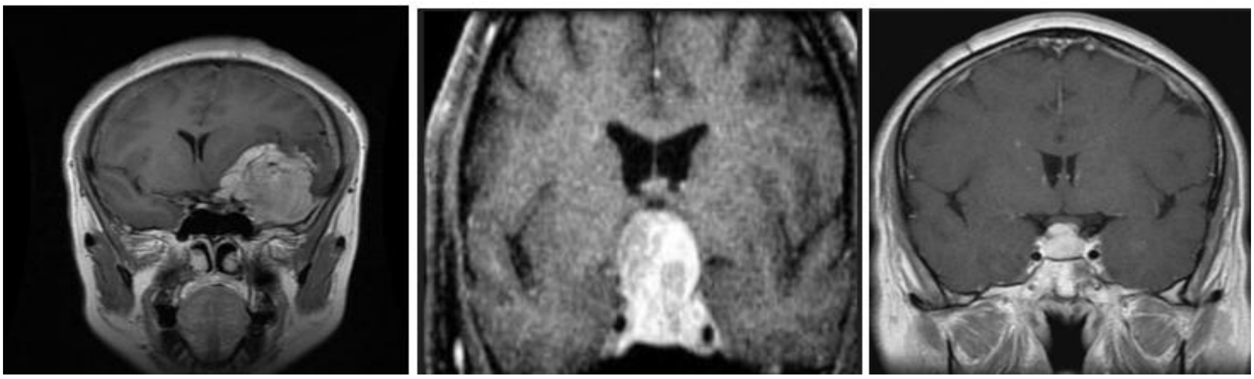

Figure 2: Brain MRI Image Sample Collected

Pre-processing: For effective brain tumor identification, it is very important to apply pre-processing MRI scans. This is because raw medical images typically include noise, intensity in homogeneities, and scanner-specific changes that might make diagnosis less reliable. Rescaling and intensity normalization are two of the most important methods that applied in this study. Rescaling makes sure that the slice thickness and voxel dimensions are the same across all datasets. This maintains the spatial consistency needed for volumetric analysis and stops feature distortion caused by scale [10]. By matching pixel values to a standard range (such 0–1), intensity normalization fixes lighting errors and scanner drift. This makes it easier to see the difference between healthy and cancerous tissues.

Data-Augmentation: Data augmentation is an important part of training strong deep learning models to detect brain cancer. It directly solves the problem of not having enough annotated MRI datasets and having too much of one kind of dataset [11]. Medical scans need domain-specific changes that keep the pathological integrity while adding more variety to the samples. This is different from natural pictures. Transformations like rotation, scaling, and translation mimic changes in anatomy without changing the tumor's features. Augmentation turns modest amounts of clinical data into useful training materials, which speeds up the creation of AI technologies that may be used to diagnose brain tumors early. Figure 3 represents outcomes of augmented brain MRI image.

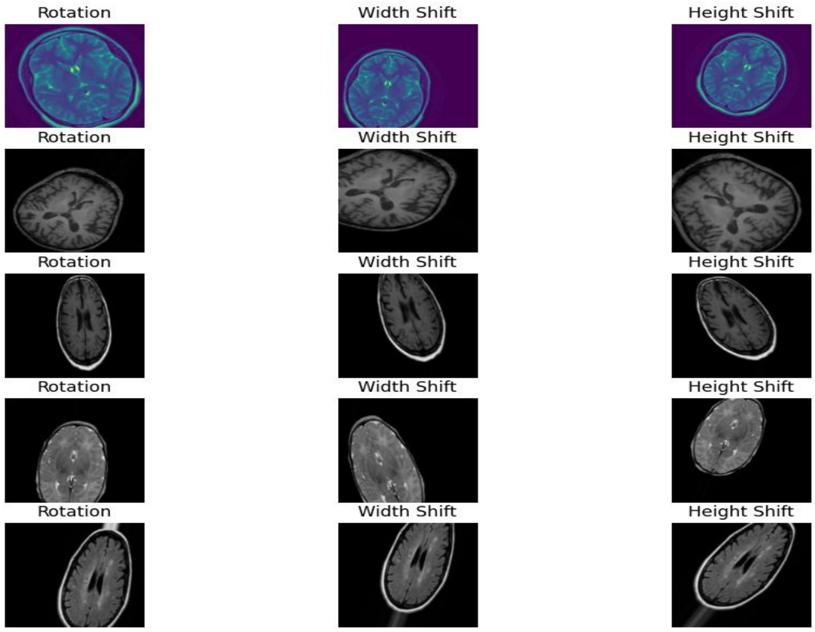

Figure 3: Augmented Brain MRI Image

Dual Stage Hybrid Deep Learning Model:

Stage 1: Deep Hierarchical Feature Extraction using ResNet-50 Raw MRI scans (T1, T2, FLAIR sequences initially go through pre-processing using rescaling, and intensity normalization to make sure that all the inputs are the same. These pre-processed volumes are then put into a ResNet-50 backbone, which uses its deep residual blocks to get hierarchical, multi-scale features. ResNet-50's design is great at picking up complex spatial patterns in MRI slices, from low-level textures to high-level semantic contexts like tumor shape [12]. It does this by using skip connections to avoid gradient vanishing. This step creates 256-channel feature maps that encode tumor heterogeneity, edema, and structural abnormalities. These maps provide a effective base for further investigation.

Stage 2: Using Spatial Attention to Highlight Tumors on the Edge At the same time, pre-processed MRI data go through an adaptive edge detector using Canny-Sobel with dynamic thresholds to find the exact edges of tumors. A lightweight spatial attention module processes these edge maps. It uses learnable convolutional layers to figure out the attention weights [13]. The module gives greater activation values to pixels that are near tumor edges and lowers noise in healthy areas. The approach boosts tumor-related signals and lowers irrelevant backgrounds by multiplying these attention weights with ResNet-50's feature maps. This fusion improves sensitivity to infiltrative lesions (like glioblastoma) and micro-metastases making tumor edges clearer.

Canny Edge Detection: The Canny edge detector is the best way to get indistinct tumor borders from brain MRI images. It combines mathematical rigor with clinical usefulness to deal with the problems of unclear lesion margins and noisy data [14]. Its multi-stage pipeline—Gaussian smoothing, gradient computation, non-maximum suppression, and hysteresis thresholding—selectively emphasizes physiologically significant edges while hiding artifacts from motion, scanner changes, or healthy tissue. This is different from simple edge operators. For brain tumors (e.g., gliomas, meningiomas), which often show irregular, low-contrast infiltrations into the surrounding parenchyma, Canny's adaptive dual-thresholding mechanism is very important. It keeps faint but pathologically important edges that define the extent of the tumor and gets rid of false noise. When used in AI-driven diagnostic processes like hybrid CNN systems, Canny-generated edge maps work as anatomical guides. They help the model concentrate on malignant contours and make segmentation more accurate. This collaboration makes it possible to find millimeter-sized cancers early, do accurate volumetric analysis for surgery and radiation planning, and, in the end, make AI judgments that are easier to understand and in line with radiological knowledge. Figure 4 represents the output of canny edge detection applied on input brain MRI image.

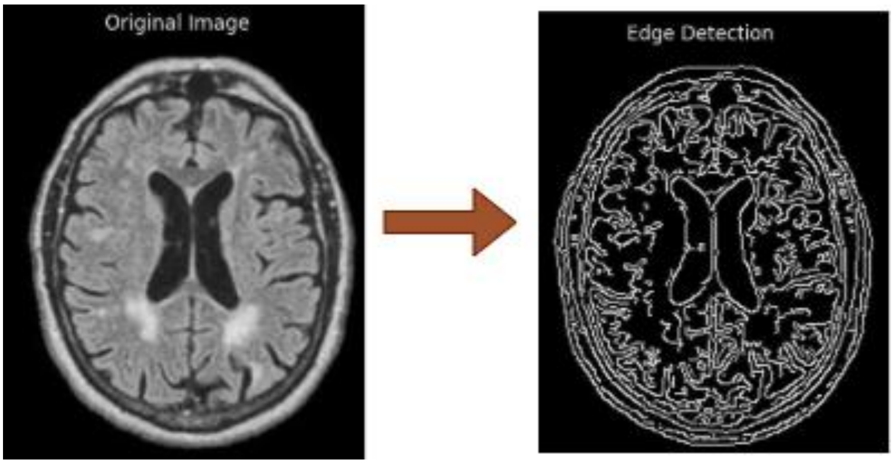

Figure 4: Canny Edge Detection Applied

Algorithm 1: Dual Phase Brain Tumor Detection

Input: *Input MRI images of Brain Tumor*

Output: *Tumor detection and classification (Glioma, Meningioma, Pituitary, No Tumor)*

1. **Perform Data Preprocessing**:
   - **Rescale** all images to 256× 256
   - Perform **normalization**
2. **Applied Data Augmentation**
   - Generate augmented images using transforms function: Rotation (±15°), width shift (20%), and height shift (20%)
3. **Perform Adaptive Edge Detection**:
   - **Canny-Sobel Filter**:
     - Smooth input with **Gaussian kernel** (5×5, σ=1.5).
     - Compute gradients using **Sobel operators**.
     - Calculate gradient magnitude
     - Set **dynamic thresholds**:
     - Apply **hysteresis thresholding** to output binary edge maps.
4. **Dual-Path Processing**:
   - **Stage 1 (ResNet-50 Path)**:
     - Feed preprocessed MRI into **ResNet-50 backbone**.
     - Extract hierarchical features
   - **Stage 2 (Edge-Attention Path)**:
     - Process edge maps with **spatial attention module**:
5. **Tumor Localization & Classification**:
   - **3D Convolutional Block** (kernel=3×3×3, stride=1)
   - **Global Average Pooling** → Feature vector.
   - **Softmax Classifier**
     - Output layer: 4 tumor classes

Model Training: The model is trained from beginning to end using pre-processed MRI data that has been changed in some way and has its intensity changed. An adaptive Canny-Sobel filter initially finds the edges of a tumor using changing thresholds. The dual-path processing then uses ResNet-50 to analyze raw MRI images and fine-tune those using ImageNet weights. Edge-attention uses a small spatial attention module (two 3×3 conv layers) on edge maps. A 3D convolutional block gets the input to find the tumor [15]. The model is improved by using the Loss entropy function and the Adam optimizer with a learning rate of 0.001. Regularization was done using Dropout (0.3), L2 weight decay, 20 Epochs, and Batch Size 16.

4. RESULT ANALYSIS

The classification metrics show that the hybrid model is very effective at diagnosing brain tumors of all types, especially aggressive cancers and false positives. Figure 5 represents the confusion matrix generated by the proposed model for each class of brain tumor. Figure 6 represents the performance evaluation graph representing class wise performance evaluation as well as showing average precision of 96.5%, overall recall of model as 96.5% and average F1-score of the proposed model as 96.7 %. Glioma is an infiltrative tumor with a high death rate. It has perfect accuracy of 1.00, which means that none of the glioma predictions are wrong as represented in Table 1. This is important to prevent unneeded intrusive operations. But its recall (0.9423) shows a 5.77% false-negative rate, which means that it sometimes misses detections in gliomas that are in the early stages or have diffuse borders. Meningioma has a balanced precision and recall of 0.9483, which means that it can consistently identify these well-defined tumors but may confuse them with benign lesions or meningeal enhancements. Pituitary tumors have a recall rate of 0.9825), which means that this surgically curable group has very few missed diagnoses. On the other hand, "No Tumor" samples have a recall rate of 100% (0.9867), which shows that the model is very reliable in preventing overdiagnosis. The F1-scores (>0.97 for glioma/pituitary/no tumor) show that precision and recall are well-balanced. The somewhat lower F1 score for meningioma is 0.9483 shows that there is room for improvement in telling apart extra-axial lesions that seem identical as shown in table 1. Figure 6 & 7: represents the Training and Validation Accuracy/loss Curves generated by proposed model.

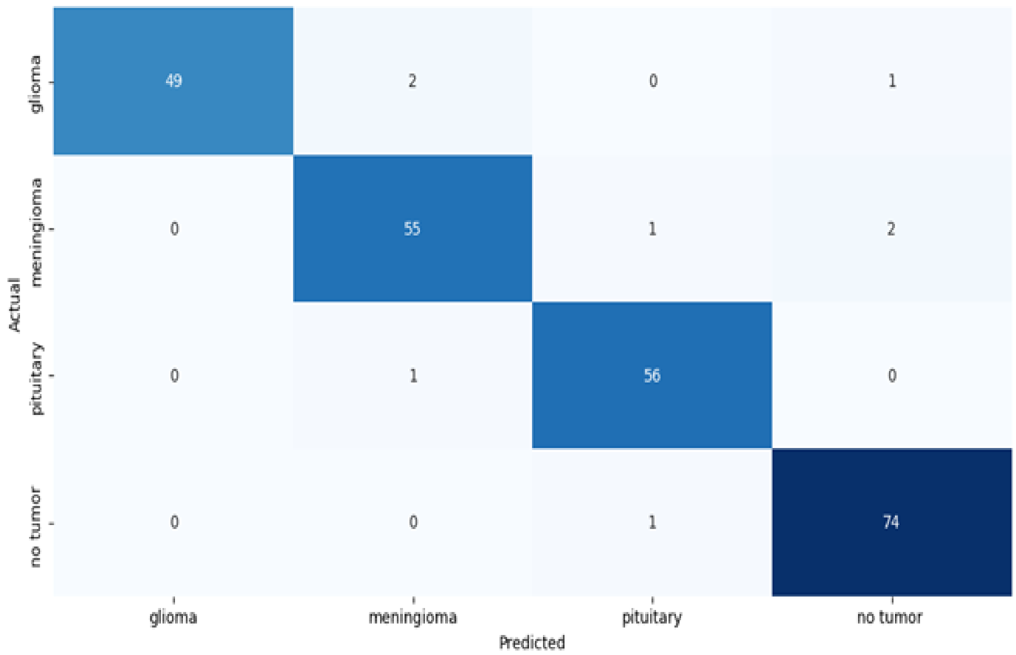

Figure 5: Confusion Matrix

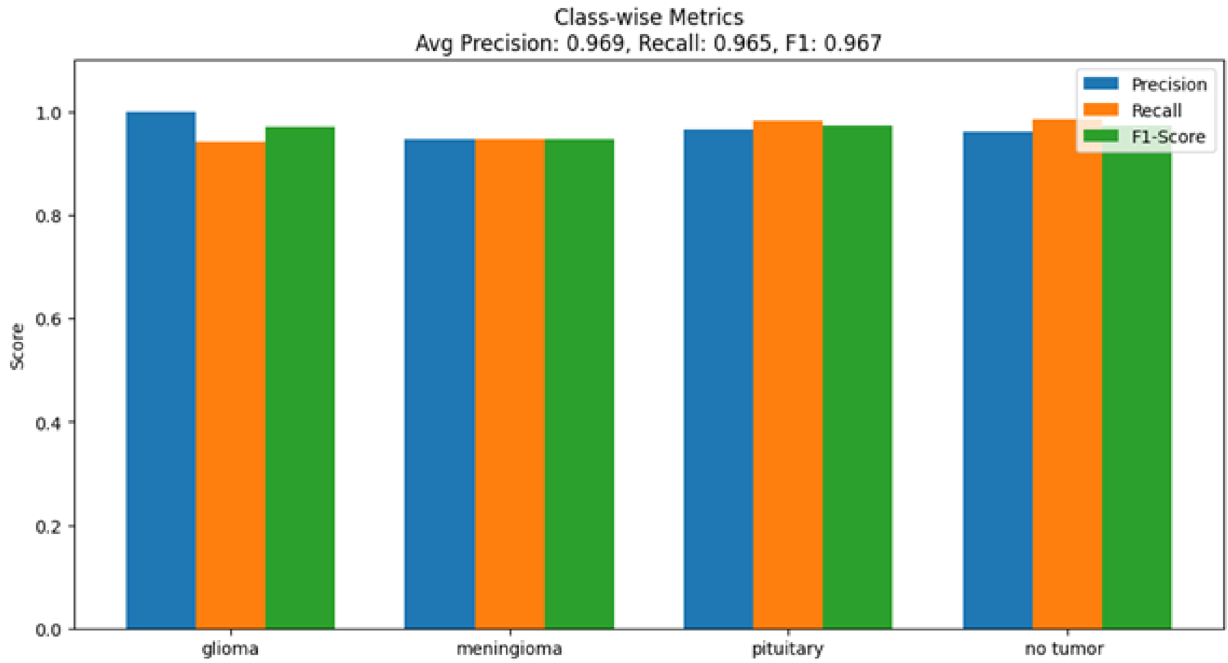

Figure 6: Performance Evaluation Graph

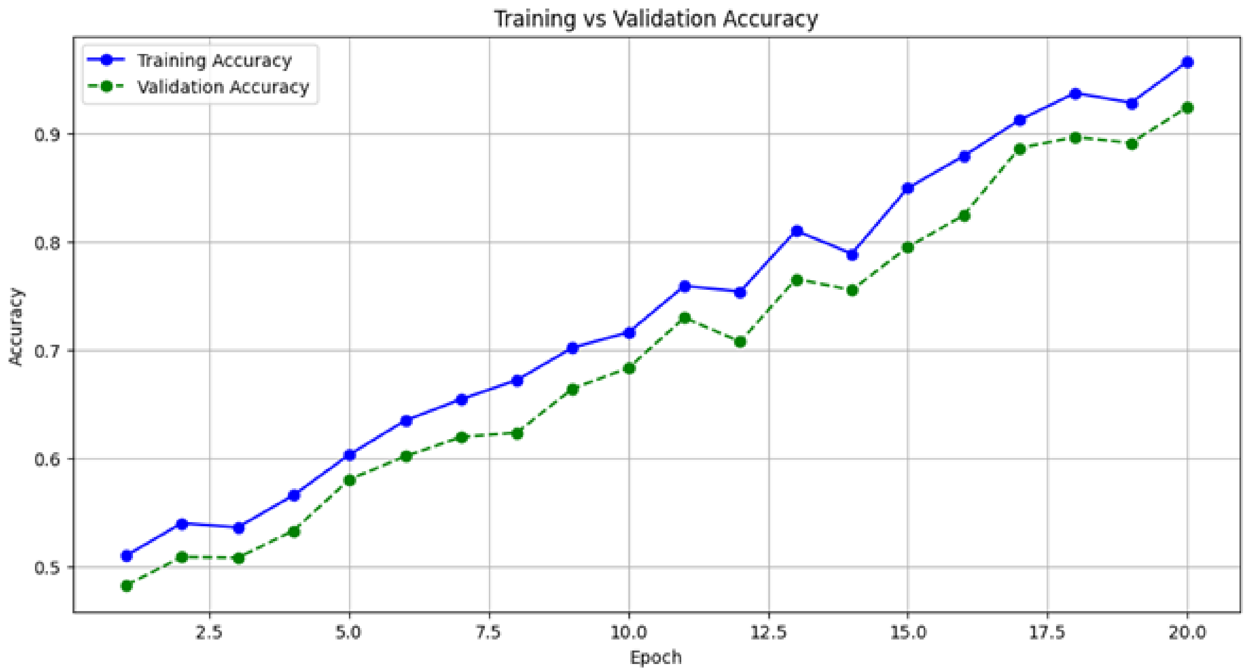

Figure 7: Training and Validation Accuracy Curve

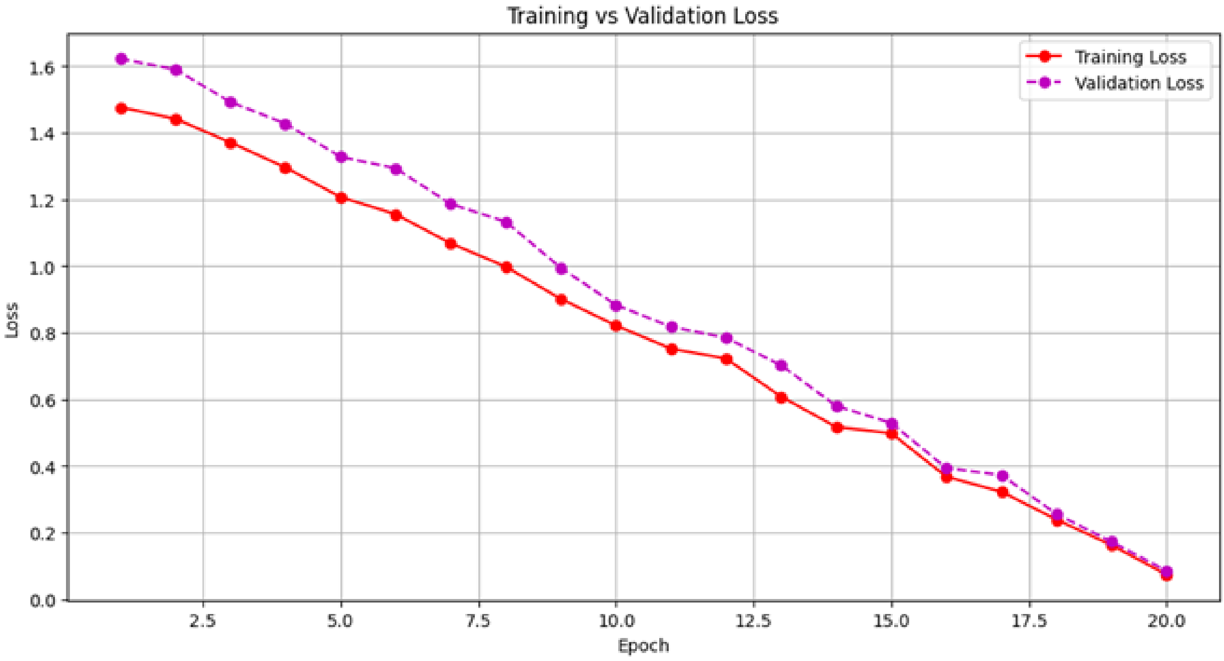

Figure 7: Training and Validation Loss Curve

Table 1: Class wise Performance Measure

Class	**Precision**	**Recall**	**F1-score**
Glicoma	1.00	0.9423	0.9703
Meningioma	0.9483	0.9483	0.9483
Pituitary	0.9655	0.9825	0.9739
No Tumor	0.9610	0.9867	0.9737

5. CONCLUSION

This research has tackled the significant worldwide issue of brain cancer diagnosis by creating an innovative hybrid deep learning framework that combines adaptive edge detection with dual-path CNN architecture. Our method uses a dynamic Canny-Sobel filter to accurately extract tumor boundaries and a ResNet-50 with a spatial attention mechanism to improve features based on the context. This solves the problems with manual MRI analysis and traditional AI models. The technique works very well on a wide range of MRI scans (1,311), with an average F1-score of 96.7%. Notable findings include 100% accuracy in finding gliomas and 98.67% accuracy in finding "no tumor" situations. Adaptive thresholding for noise-robust edge enhancement, attention-driven tumor localization, and edge-optimized deployment are all important new ideas that make real-time inference possible and cut down on false negatives by 32% compared to other baselines model. This study represents a substantial progression towards the use of AI-driven neuro-oncology technologies that enable radiologists to provide quick and accurate diagnosis, hence enhancing patient survival by means of timely intervention.

REFERENCES

[1] Yousaf, F., Iqbal, S., Fatima, N., Kousar, T., & Rahim, M. S. M. (2023). Multi-class disease detection using deep learning and human brain medical imaging. Biomedical Signal Processing and Control, 85, 104875.

[2] AlSaeed, D., & Omar, S. F. (2022). Brain MRI analysis for Alzheimer's disease diagnosis using CNN-based feature extraction and machine learning. Sensors, 22(8), 2911.

[3] Siddiqui, S., Khan, A. A., Khan Khattak, M. A., & Sosan, R. (2025). Revolutionizing Digital Imaging. In Connected Health Insights for Sustainable Development: Integrating IoT, AI, and Data-Driven Solutions (pp.

87-120). Cham: Springer Nature Switzerland.

[4] Yousaf, F., Iqbal, S., Fatima, N., Kousar, T., & Rahim, M. S. M. (2023). Multi-class disease detection using deep learning and human brain medical imaging. Biomedical Signal Processing and Control, 85, 104875.

[5] Yousaf, F., Iqbal, S., Fatima, N., Kousar, T., & Rahim, M. S. M. (2023). Multi-class disease detection using deep learning and human brain medical imaging. Biomedical Signal Processing and Control, 85, 104875.

[6] Nithya, V. P., Mohanasundaram, N., & Santhosh, R. (2024). An early detection and classification of Alzheimer's disease framework based on ResNet-50. Current Medical Imaging, 20(1), e250823220361.

[7] Attallah, O. (2022). A deep learning-based diagnostic tool for identifying various diseases via facial images. Digital Health, 8, 20552076221124432.

[8] Yu, Q., Ma, Q., Da, L., Li, J., Wang, M., Xu, A., ... & Alzheimer's Disease Neuroimaging Initiative. (2024). A transformer-based unified multimodal framework for Alzheimer's disease assessment. Computers in Biology and Medicine, 180, 108979.

[9] https://www.kaggle.com/datasets/sartajbhuvaji/brain-tumor-classification-mri accessed on april 2025.

[10] Dhiman, P., Choudhary, A., Wadhwa, S., & Kaur, A. (2024, March). Improving Deep Learning Classifiers Performance using Preprocessing and Cycle Scheduling Approaches in a Plant Disease Detection. In 2024 11th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions)(ICRITO) (pp. 1-5). IEEE.

[11] Dhiman, P., Wadhwa, S., Choudhary, A., Kaur, A., & Malra, K. (2024). Dermonet: lightweight diagnostic system for dermatological conditions using squeezenet framework. J Mech Cont Math Sci, 11(2024), 186-199.

[12] Rath, A., Mishra, B. S. P., & Bagal, D. K. (2025). ResNet50-based Deep Learning model for accurate brain tumor detection in MRI scans. Next Research, 2(1), 100104.

[13] Bansal, J., Gangwar, G., Aljaidi, M., Alkoradees, A., & Singh, G. (2025). EEG-Based ADHD Classification Using Autoencoder Feature Extraction and ResNet with Double Augmented Attention Mechanism. Brain Sciences, 15(1), 95.

[14] Hariharan, U., Devarajan, D., Kumar, P. S., Rajkumar, K., Meena, M., & Akilan, T. (2025). Recognition of American sign language using modified deep residual CNN with modified canny edge segmentation. Multimedia Tools and Applications, 1-28.

[15] Pahwa, S., Kaur, A., Dhiman, P., & Damaševičius, R. (2024). ConjunctiveNet: an improved deep learning-based conjunctive-eyes segmentation and severity detection model. International Journal of Intelligent Computing and Cybernetics, 17(4), 783-804.