International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 21s, 2025
https://theaspd.com/index.php

Enhancing Early Brain Tumour Diagonsis Using Active Contour Algorithm Integrated With Swin Preprocessing And Canny Edge Detection

Ms. Vertika Agarwal[1], Ms. Shalini Verma[2], Ms. Geetanjali Tyagi[3], Ms. Rupam Kumari[4], Dr.Niharika Saxena[5]
[1]Assistant Professor CSE, SRM IST DELHI-NCR MODINAGAR CAMPUS GHAZIABAD 201204,India,Vertika.agarwal21@gmail.com
[2]Assistant Professor CSE, SRM IST DELHI-NCR MODINAGAR CAMPUS GHAZIABAD 201204,India, shalini.verma0164@gmail.com
[3]Assistant Professor CSE, SRM IST DELHI-NCR MODINAGAR CAMPUS GHAZIABAD 201204,India,git101288@gmail.com.
[4]Assistant Professor CSE, SRM IST DELHI-NCR MODINAGAR CAMPUS GHAZIABAD 201204,India,rupamrce23@gmail.com
[5]Assistant Professor CSE, SRM IST DELHI-NCR MODINAGAR CAMPUS GHAZIABAD 201204, India,niharikasaxena2303@gmail.com

Abstract
Early and accurate detection of brain tumour is critical for effective treatment planning and improved patient prognosis. Traditional image segmentation techniques often struggle with low-resolution or noisy medical images, leading to imprecise localization of tumour boundaries. To address these limitations, this research proposes a novel framework that enhances the performance of classical contour-based segmentation by integrating ***SwinIR (Swin Transformer for Image Restoration)*** *with* ***Canny edge detection*** *and* ***Active Contour Models (Snakes)****. SwinIR, a transformer-based image enhancement technique, improves image clarity and resolution by capturing hierarchical contextual features, enabling better identification of tumour structures. The enhanced images are further refined using Canny edge detection and segmented via active contours to isolate tumour regions effectively.*
The proposed method is validated using 10 brain CT images from the BraTS 2021 dataset, and its performance is evaluated using ***Pixel Accuracy*** *and* ***Abnormality Ratio****. Experimental results demonstrate that SwinIR-preprocessed images yield the highest pixel accuracy of 97.12%, outperforming traditional approaches. Additionally, the framework improves the abnormality ratio by accurately highlighting tumour-affected regions. This integration of deep learning-based enhancement with classical segmentation offers a promising approach for more accurate and interpretable brain tumour diagnosis, paving the way for its application in clinical decision-support systems.*

INTRODUCTION

Brain tumourrepresent one of the most critical and life-threatening forms of neurological disorder which necessitates early and accurate diagnosis to improve patient outcomes. Traditional diagnostic approaches rely heavily on manual interpretation of MRI or CT scan images, which are time-consuming and prone to variability among radiologists.

As a result, creating automated and precise image analysis methods has emerged as a key area of study for artificial intelligence and medical imaging. The brain is a vital and intricate organ that regulates the nervous system. A brain tumour may result from aberrant and unchecked brain cell development. Primary and secondary tumour are the two general categories into which brain tumour fall. Brain tumourhave the highest cancer mortality rate in the world, and their development cannot be determined by growth rate. While secondary brain tumouroriginate elsewhere in the body and spread to the brain through blood flow, primary brain tumourare created in the brain tissues. Early detection of brain tumour is challenging. Furthermore, these may become severe illnesses if not were done in a timely fashion. The technological advancement of MRI in the neuro imaging sector has given more and more important information on how the human brain functions. But healthcare professionals have been faced with severe challenges in managing MRI data due to the tedious and laborious task of pulling out information of significance from complex and large MRI databases. Manual interpretation is subject to error. It is also labour-intensive, especially because of the large number of inter- and intra-operative variations which are intrinsic to MRI tests. Brain tumour is not easy to diagnose due to the different characteristics of brain tumour images in different scans which vary in edges, shapes, and textural characteristics. These characteristics results in

brain cancer diagnosis, a challenging task. Hence, it is essential to design computer-based techniques which will provide more effective and immediate response for Brain tumour detection and diagnosis.
In recent years, computer-aided diagnosis (CAD) systems have made substantial progress by leveraging deep learning and advanced image processing algorithms. Among these, **segmentation-based methods** are particularly important for identifying the precise location and shape of tumour regions. However, classical segmentation methods such as edge detection or contour evolution often suffer from low robustness and sensitivity to noise, especially in low-resolution or artifact-laden images.
To address these challenges, this research proposes a novel framework that combines SwinIR-based image enhancement with Active Contour Models (Snakes) and Canny Edge Detection for precise and early detection of brain tumours. The SwinIR (Swin Transformer for Image Restoration) module enhances the visual quality of medical scans by capturing both global and local contextual features, effectively highlighting tumour boundaries. This enhanced image is then processed through Canny edge detection and segmented using the active contour algorithm to delineate tumour regions with high precision.
The proposed method is tested on brain images from the **BraTS 2021 dataset**, and performance is evaluated using two critical metrics: **Pixel Accuracy** and **Abnormality Ratio**. Results show that SwinIR-enhanced images significantly improve the effectiveness of contour-based segmentation techniques, leading to more reliable detection of abnormal regions.
This paper is organized as follows: Section 2 presents the related work; Section 3 outlines the proposed methodology, including SwinIR preprocessing and segmentation pipeline; Section 4 discusses the results and evaluation; and Section 5 concludes the study with potential directions for future work.

LITERATURE REVIEW

Alsaif, H., et al [2] represents a detailed review of various CNN architectures such as ResNet, AlexNet, and VGG.The highest accuracy of almost 96% for the VGG 16 model was attained by G Researchers uses techniqueto enhance the MRI size called as data augmentation(H, 2022. Ismaila et al [3] performs the identification of functional brain networks to preserve the patient neurological functions and boost the detection of functional brain networks in rs-fMRI data.Using fMRI images, researchers identify seven primary functional brain networks, with the suggested deep learning architecture achieving the best performance of 75% (Ismaila, 2022). Rasheed et al[4] explores the potential of Deep learning algorithm and present a novel methodology integrating image enhancement techniques, specifically, Gaussian-blur-based sharpening and Adaptive Histogram Equalization using CLAHE, with the proposed model.Both cases without tumors and several kinds of brain cancers, including pituitary, meningioma, and glioma, are analyzed and theexperimental results of the suggested method showed 97.84% classification accuracy, 97.85% precision success rate, 97.85% recall rate, and 97.90% F1.Rasheed (2023). Abdusalomov, et al [5] discussed the fine tuning of YOLOv7 model through transfer learning in detecting gliomas, meningioma, and pituitary brain tumors. Proposed approach achieved accuracy of 99.5% and show optimal performance in detection of small tumours as compared to traditional approach. (Abdusalomov, 2023). Stathopoulos et al [6] evaluate the diagnostic performance of six fundamental MRI sequences in detecting tumor-involved brain slices using four distinct CNN architectures (Mobile net, VGG NET, RESNET AND INCEPTION) enhanced with transfer learning techniques.62 patients' exams yielded 1646 MRI slices, including both tumor-bearing and normal findings.. Classification accuracy of 98.6 has been achieved. (Stathopoulos, 2024).Li et al [8] explores deep learning models ResNet-50, Xception, and InceptionV3 augmented with , Gradient-weighted Class Activation Mapping (Grad CAM) and Stream lit to enhance the detection capability of Brain tumour MRI scans. 99% of efficiency is achieved with proposed framework. (Li, 2024).
Malla et al [8] uses deep convolutional neural network (DCNN) for diagnosis of brain magnetic resonance imaging (MRI) images of meningioma tumors, glioma tumors, and pituitary tumors.To prevent overfitting and vanishing gradient problems, a pre-trained CNN architecture is modified and a Global Average Pooling (GAP) layer is placed at the output layer.
.. The testing accuracy of the suggested architecture is 98.93% (Malla, 2023). Almijalli et al [9] proposed segmentation method which is made up of an active contour algorithm, an anisotropic diffusion filter for pre-processing, active contour segmentation (Chan-Vese), and morphologic operations for segmentation refinement.The researcher obtained a 96% improvement in performance metrics, including accuracy, precision, sensitivity, specificity, Jaccard index, Dice index, and Hausdorff distance, when compared to the conventional segmentation method.Almijalli, 2025).Zahoor et al[10]explores the complete pipeline

for detection and classification of Brain tumour in individual from MRI scans.CNN and classifiers based on ensemble machine learning are used to identify whether tumors exist or not. The second phase then takes these pictures and divides them into four classifications: normal, pituitary, meningioma, and glioma. In terms of dynamic features and the gradient of histograms (HOGs) It has been suggested that we use a convolutional neural network (CNN) called Brain Region-Edge Net (BRAIN-RENet) to analysis images from various software platformsand obtained F1-Score (0.9909), accuracy (99.20%), precision (0.9906), and f recall (0.9913) in the CE-MRI data set. (Zahoor, 2022).Liu et al [11] provides a comprehensive overview for MRI-based brain tumor segmentation methods. Researcherstudiesbrain tumor imaging methods, preprocessing operations.Covered are the assessment and verification of the MRI brain tumor segmentation results.. Liu (2014). Sharma et al[12] discusses a a new approach of level set with respect to polynomial approach with k-means and fuzzy c-means algorithm. The researcher locates the brain tumor portions with high recall, accuracy, and precision by using polynomial-based level set segmentation to provide the appropriate ROI. Sharma (2017).

Megala G et al [13] explores DeepGAN , neural network used for identifying and detecting brain Tumors in the MRI images of patients.The generator and discriminator of the proposed model receive the preprocessed raw MRI images in order to detect a tumor and extract significant features. Calculating the precision, recall, specificity, sensitivity, and accuracy of the proposed model yields 99% accuracy (G, 2023).Biratu et al [14] provides comprehensive survey of three, recently proposed, major brain tumor segmentation and classification model techniques, namely, region growing, shallow machine learning and deep learning.

Practical topics covered includedatasets, feature extraction, and pre- and post-processing approaches,the benefits and drawbacksof various strategies, and metrics for assessing the models' performance. (Biratu 2021).YOLOv5s-ASPP, YOLOv5s-CBAM, YOLOv5s-CA, YOLOv5s-ASPPCBAM, and YOLOv5s-ASPP-CA are some of the optimized versions of the original YOLOv5 algorithm that were produced by Yang T et al. [15] after they investigated a number of optimizations to the algorithm and introduced Atrous Spatial Pyramid Pooling (ASPP), Convolutional Block Attention Module (CBAM), and Coordinate Attention (CA) for structural improvement. The sets for training and validation are utilized for 100 iterative training rounds were entered intofive models that have been optimized,

, the YOLOv8s model, and the YOLOv5s model. The best weight file of the model with the best performance was used for the test set's final test evaluation index for each of the six models that were trained (YangT, 2025). Shoaib et al. [16] investigate the use of softmax activation in conjunction with convolutional neural network (CNN) models DenseNet201, EfficientNetB5, and InceptionResNetV2 for feature extraction. For dimensionality reduction, Principal Component Analysis (PCA) has been used. After that, three machine learning models were created for the classification process: Support Vector Machine (SVM), Multi-layer Perceptron (MLP), and Gaussian Naive Bayes (GNB).The findings demonstrate that when paired with SVM and MLP, DenseNet201 performs better than the other models in terms of accuracy and recall.It also exhibits the highest efficacy when paired with SVM and MLP, which is close to 100%. (Shoaib, 2025).Mishra et all[17] proposed modified MASCA–PSO(modified adaptive sine cosine optimization algorithm- particle swarm optimization) based LLRBFNN (local linear radial basis function neural network) model for classification of benign and malignant tumors. The weights of the LLRBFNN model are optimized using the proposed MASCA–PSO method, providing a novel solution to do away with the time-consuming manual detection radiologists' duty.

When comparing the classification accuracy results from the particle swarm optimization based LLRBFNN models with those from the adaptive sine cosine optimization algorithm, PSO, and sine cosine optimization algorithm, the suggested MACSA–PSO based LLRBFNN model performs better than the other LLRBFNN based models.(Mishra, 2019).Hekmat et al [18] proposed a robust ensemble approach which uses Differential Evolution (DE)-based algorithm for three high performing pre-trained CNN models like MobileNetV1, MobileNetV2, ResNet50V2 and optimizes their contributions by assigning optimal weights through DE.Method cleverly modifies weight of the model distributionto maximize the performance of the group..Using two publicly accessible datasets—a multiclass (4-class) dataset and a binary classification dataset (BR35H)—the optimized ensemble strategy performed better in terms of accuracy, achieving 98% and 97.03%, respectively.Hekmat (2025).Three CNN models are proposed by Irmak et al. [19] to perform multiclassification of brain tumors for the purpose of early diagnosis.The first CNN model has a 99.33% accuracy rate in detecting brain cancers. Pituitary, glioma, meningioma, normal, and metastatic are the five categories of brain tumors that the second CNN model can distinguish with an accuracy rate of 92.66%.and the third CNN model has an accuracy rate of 98.14% in classifying brain tumors into three grades: Grades II, III, and IV. The grid search optimization approach is used to choose the hyperparameters for the CNN models. Irmak (2021).

Jabbar et al [20] proposed the Caps-VGGNet hybrid model, which integrates the CapsNet model with the VGGNet model by adding the layers of VGGNet.Large datasets are a challenge that the model gets around by automatically extracting and classifying features.
High-quality pictures of brain tumors from the Brats-2020 and Brats-2019 datasets have been used.In terms of accuracy, specificity, and sensitivity, it demonstrated the best level of performance and greater efficacy when compared to other conventional and hybrid models. Jabbar (2023) reports that the suggested hybrid model achieved 0.98 sensitivity, 0.99 specificity, and 0.99 accuracy.
. To effectively classify tumors, Khushi et al. [21] suggest using a pre-trained EfficientNetb4 model with a customizable callback and an adjustable learning rate.Researchers improve the amount and quality ofutilizing the Br35h dataset, which is available to the public, using data augmentation methods .For Br35h, the model's sensitivity, specificity, precision, NPV, FOR, and F1-score are 99.33%, 99.97%, 99.93%, 99.33%, 0.66%, and 99.66%, in that order.The FNR and FPR of the augmented Br35H dataset were 0.66% and 0%, respectively. (Khushi, 2024). Muhammad et al [22] presents a survey paper, on state of-the-art convolutional neural network models for BTC (Brain tumour classification) by performing extensive experiments using transfer learning with and without data augmentation. The researcher outlines the benchmark data sets that are available for evaluating Bitcoin and points out important obstacles, like the dearth of end-to-end deep learning models with publicly available data sets.
Additionally, they provide particular suggestions for further research in the area of Bitcoin, such as examining edge/fog/cloud computing with FA, sophisticated dataenrichment methods, model explainability and confidence, IoMT, and a careful analysis of sequential and transfer learning procedures. These will increase the Bitcoin techniques' degree of maturity, make them more suitable for commercial clinical applications, and make it easier for them to integrate with smart healthcare (Muhammad, 2020).
Khan et al [23], presented a unparalled deep learning approach which introduced three additional layers in residual block. These layers preserve all pertinent data produced by the model while seamlessly relaying featuresfrom the leftover block to the backbone network.In addition to standard convolutional layers, the researcher's enhanced architecture included a residual block with a separable convolution layer. Swish, which improves information retention and expands feature generation, has taken the place of ReLU. The effectiveness and adaptability of the suggested methodhave been assessed using the Figshare Multiclass and BR35H Binary Class benchmark datasets, which are both publicly accessible and comprise 3063 and 3000 sample images, respectively. With an accuracy of 99.83% on the BR35H binary dataset and 96.95% on the Figshare multiclass dataset, the model performs better on the benchmark dataset than other pre-trained models (Khan, 2025).
Ghosh et all[24] employed many ML algorithm to detect the presence of Brain Tumour and if present then performs classification.The MRI images were classified using nine machine learning algorithms such as Logistic Regression, Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Naive Bayes (NB), Decision Tree (DT), Random Forest, XGBoost, Stochastic Gradient Descent (SGD), and Gradient Boosting classifiers Accuracy, recall, precision, F1-score, AUC-ROC curve, and AUC-PR curve are among the performance metrics that have been measured. With 92.4% accuracy, 94.4% recall, 85% precision, 89.5% F1-score, 97.2% AUC-ROC, and 91.4% AUC-PR, the Gradient Boosting classifier has outperformed all alternatives. To tackle the multi-class classification problem, four machine learning algorithms have been employed: SVM, KNN, Random Forest classifier, and XGBoostclassifier.Every other method has been surpassed by the XGBoost classifier in terms of accuracy, precision, recall, and F1-score. Four machine learning algorithms—SVM, KNN, Random Forest classifier, and XGBoost classifier—have been used to solve the multi-class classification problem.In terms of accuracy, precision, recall, and F1-score, the XGBoost classifier has outperformed every other algorithm. (Ghosh, 2021).Patil et al[25] proposed first shallow convolutional neural network (SCNN) and VGG16 network with T1C modality MRI image and subsequently loss and accuracy were examined.The deep learning models from both were coupled with features that were retrieved to improve the classification accuracy of three tumor kinds. Combining deep learning models increases many classes' accuracy. both the classification problem and the overfitting of the model to the imbalance of the dataset. The proposed model's classification accuracy was 97.77% Patil (2023).

Using a range of machine learning techniques, Researcher (Verma, 2024)[28] investigate the segmentation of brain tumors and the classification of anomalies in MRI images. Different data points were extracted and analyzed from 42 studies that met the inclusion criteria.

3.PROPOSED METHODOLOGY:

3.1 Material:

Ten brain images from the Brain Tumour Segmentation Challenge BraTS 2021 datasets has been employed to carry out proposed research work(https://www.kaggle.com/datasets/dschettler8845/brats-2021-task1).Swin-IR preprocessing method is distinct from traditional preprocessing metod as it utilizes Transformer based approach. Proposed method includes improving contour algorithm with Swin-Ir and Canny edge detection.Swin-Ir Preprocessing requires more GPU power so A100 GPUruntimeisemployedto process 10 images which requires approximately 10 minutes.Further processing with Canny edge detection is carried out with runtime type T4 GPU in Google Colab.

The following block diagram Figure 1 represents the proposed method for Early brain tumour detection.

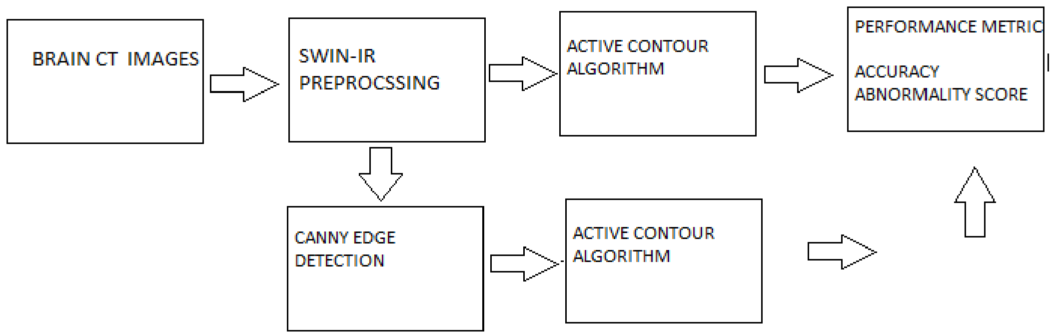


Figure 1:Flow chart of Proposed method

3.2 Active Contour Algorithm (Snakes) :

In the field of image segmentation, Active Contour Algorithms, also known as Snakes(Sefti, 2025)[1], are used to identify object boundaries. They function by causing a curve (snake) to evolve under the influence of external forces (derived from the image data) and internal forces (related to the curve's shape) until it converges on the desired object boundary.The Active Contour Model (ACM), another name for the original snake, is a parametric curve that moves through an image's spatial domain in order to minimise an energy functional. Based on internal and external forces, this energy functional directs the snake to align with features of interest, like object boundaries.

Mathematical Formulation:

A snake is a curve C represented by a vector function(Sefti, 2025)[1]:

$v(s) = (x(s), y(s))$, where $s \in [0, 1]$

The total energy functional E_snake is given by:

$$E\_snake = \int [E\_int(v(s)) + E\_image(v(s)) + E\_con(v(s))]\, ds \quad (1)$$

Where:
- E_int: Internal energy — enforces smoothness and continuity.
- E_image: Image energy — attracts the snake to image features like edges or lines.
- E_con: External constraint energy — optional, used to guide the snake using higher-level knowledge.

Internal energy is formulated as:

$$E\_int = \alpha(s)\ |v'(s)|^2 + \beta(s)\ |v''(s)|^2 \qquad (2)(Sefti, 2025)[1]$$

Where:
- $\alpha(s)$: Elasticity parameter (controls stretching)
- $\beta(s)$: Rigidity parameter (controls bending)

The image energy typically uses image gradients:

$$E\_image = -|\nabla I(x, y)|^2 \quad (3)$$

The Euler-Lagrange equation from calculus of variations gives the snake's equilibrium as:

$$\alpha v''(s) - \beta v^{(4)}(s) - \nabla E\_image = 0 \quad (4)$$

In dynamic form, the evolution of the snake is governed by:

$$\partial v(s, t)/\partial t = \alpha v''(s) - \beta v^{(4)}(s) - \nabla E\_image \quad (5)$$

Where the snake evolves over time t and stabilizes when $\partial v/\partial t = 0$, i.e., the internal and external forces are balanced.

This classical model is widely used for edge-based segmentation and is particularly sensitive to initialization and parameter selection.

3.3 Swin Transformer-Based Image Enhancement
Swin Transformer(Liang, 2021)[26] is a hierarchical vision transformer that computes self-attention within shifted windows across an image. It excels in modeling both local and global contextual information.Unlikely, a traditional image enhancer, Swin Transformer enhances image analysis by generating important feature representations that are crucial for tasks like segmentation, detection, and classification.It uses Hierarchical Feature Extraction which partitioned the input image into non-overlapping patches.These patches are embedded into vectors and passed through Swin Transformer blocks.Each block works on local information using window-based self-attention, while the shifting mechanism allows for cross-window communication.It performs Image Enhancement via Feature Representation.Instead of modifying pixel values directly, Swin Transformer enhances useful features byLearning attention maps that highlight regions of interest and Integrating contextual information from both fine and coarse image regions.It reduces noise and projects structures like edges or lesions via learned filters.
SwinIR consists of three main parts:
1. Shallow Feature Extraction: Extracts initial image features using a convolutional layer.
2. Deep Feature Extraction: Stacks several Residual Swin Transformer Blocks (RSTBs).
3. Reconstruction: Uses convolutional or upsampling layers to restore or enhance the image.

Mathematical Formulation
Let the input low-resolution image be denoted as:
$I_{LR} \in \mathbb{R}^{H\times W\times C}$(Liang, 2021)[26] (6)
Where H, W, and C denote the height, width, and number of channels.

The shallow feature is extracted as:
$F_0 = Conv(I_{LR})$ (7)
The deep feature extraction process with n RSTBs is:
$F_D = RSTB_n(\ldots RSTB_2(RSTB_1(F_0))\ldots)$ (8)

Each RSTB includes Swin Transformer Layers (STLs), which are formulated as:
$STL(x) = MLP(LN(W\text{-}MSA(LN(x))) + x)$(Liang, 2021)[26] (9)
Where: - LN is Layer Normalization
- MSA is Multi-Head Self Attention with Shifted Windows
- MLP is a feed-forward network

The final reconstructed high-resolution image is:

I_{SR} = Conv(F_D + F_0) (10)

Swin model employs Shifted Window Mechanism which uses non-overlapping windows to compute self-attention, reducing complexity from $O(N^2)$ to $O(M^2)$ where M << N. To enable cross-window connections, it shifts the windows between successive layers.The model is trained with L1 or L2 loss(Liang, 2021)[26]:

L = ||I_{SR} - I_{HR}||_1 (11)

Where I_{HR} is the ground truth high-resolution image.

3.4 Canny Edge Detection

The Canny Edge Detector(Sekehravani, 2020)[27] is a multi-stage edge detection algorithm developed by John F. Canny in 1986. It is widely used in computer vision to identify a wide range of edges in images.Canny algorithm has low error rate which results in fine detection of edges. It discovers all possible edges which are in close proximity to each other

Mathematical Formulation

Canny edge detection uses a Gaussian filter to smooth the image and reduce noise. The Gaussian filter is given by:

$G(x, y) = (1 / (2\pi\sigma^2)) * \exp(-(x^2 + y^2) / (2\sigma^2))$(Sekehravani, 2020)[27] (12)

The smoothed image Is = I * G, where * denotes convolution.

After noise removal ,gradient calculation is performed using Sobel operators:

Gx = I * [[-1 0 1], [-2 0 2], [-1 0 1]]

Gy = I * [[-1 -2 -1], [0 0 0], [1 2 1]]

Gradient magnitude: $G = \mathrm{sqrt}(Gx^2 + Gy^2)$(Sekehravani, 2020)[27] (13)

Gradient direction: $\theta = \arctan(Gy / Gx)$(Sekehravani, 2020)[27] (14)

It employs double thresholding technique to remove irrelevant features. Hysteresis is also used for Edge Tracking.Weak edges connected to strong edges are retained and All other weak edges are suppressed.

3.5Performance evaluation metrics

Analysis of experiment was carried out for following measures:

3.5.1: Pixel Accuracy:It measures the efficiency of proposed framework to correctly classify each pixel.

Accuracy=TP+TN (Processed Brain tumour images) /TP+TN+FP+FN

Where TP is true positive, TN is True negative,FP is False positive and FN is False negative.

3.5.2:**Abnormality Ratio**:It is also called the abnormality region ratio or tumour-to-brain ratioand is used to quantify how much of the brain is affected by the tumour. It gives a measure of the extent of abnormal (tumour) region relative to the entire brain region or image.

Abnormality ratio=Area of Tumour region(in pixels)/Total Area of Brain image(in pixel)

EXPERIMENTAL RESULT:This section elaborates the finding of Proposed Framework.Figure 2,3and 4 visualizes the Pixel accuracy for Brain images processed with Original Contour algorithm ,Pixel accuracy for Swin Processed Brain images and Pixel accuracy for Swin integrated Canny Processed Brain images.

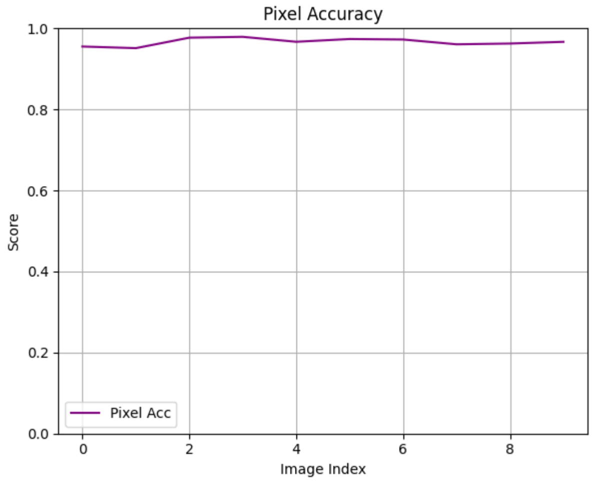


Figure2 :NORMAL BRAIN IMAGESPROCESSED WITH CONTOUR ALGORITHM

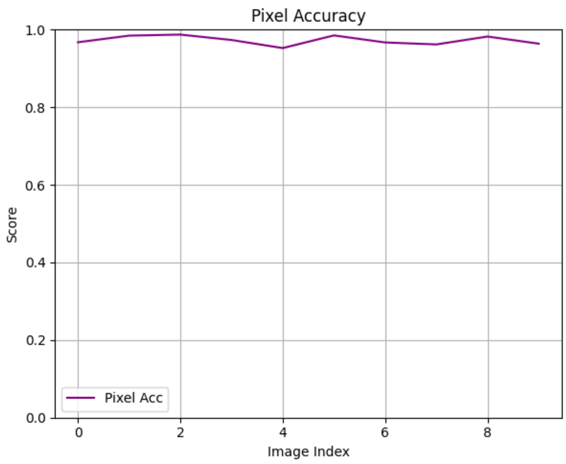


Figure 3: SWIN INTEGRATED CONTOUR ALGORITHM

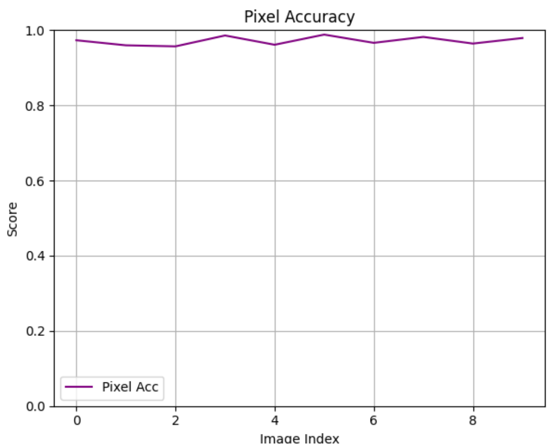


Figure 4:CANNY COMBINED WITH SWIN INTEGRATED CONTOUR ALGORITHM

Comparison of the aforementioned three techniques is illustrated in Table 1. It reveals that the pixel accuracy of Swin-processed brain images is the highest, measuring at .9712. The average pixel accuracy demonstrates an enhancement when compared to brain images that have not undergone Swin processing.Furthermore, the integration of Swin processing with Canny Edge detection also yields notable improvements.This indicates that the Swin transformer not only enhances the overall precision of pixel classification but also synergistically combines with established edge detection methods to produce superior outcomes .

Table 1

IMAGES	Average abnormality ratio	Average pixel accuracy
NORMALBRAIN IMAGES	.0264	.9705
SWIN PROCESSED IMAGES	.0014	.9712
SWIN+ CANNY INTEGRATED MODEL	.0202	.9708

Abnormality ratio elucidates the extent of the affected region within the brain. This metric is employed to distinguish between typical and healthy brain images. In our proposed framework, we have utilized brain tumour CT images, rendering the value of the abnormality ratio invariably greater than zero. The images processed by Swin distinctly delineate the compromised areas, thereby identifying the significant regions of affliction, which cannot be achieved with standard brain images.Furthermore, the heightened precision afforded by the Swin model allows for a more nuanced analysis of the tumour's morphology and interaction with surrounding neural structures.Figure 5 and 6 projects the clear validation of our proposed framework.Highest Average pixel accuracy is achieved for Swin processed images.Abnormality ratio is highest for unprocessed images.

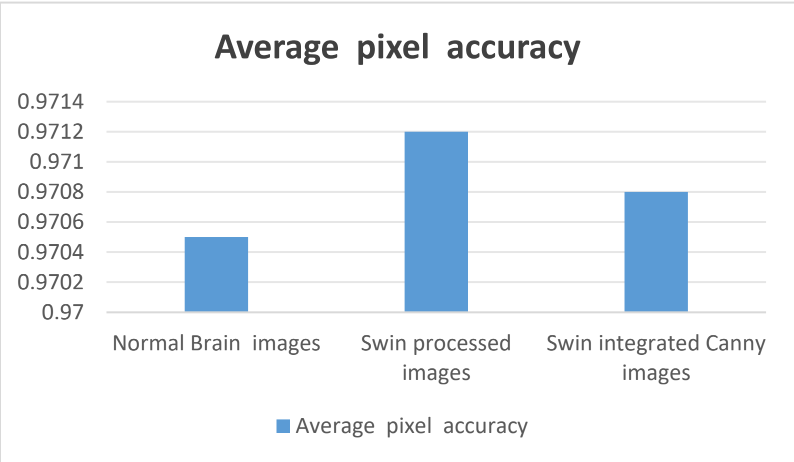


Figure 5: Averagepixel accuracycomparison between three approaches

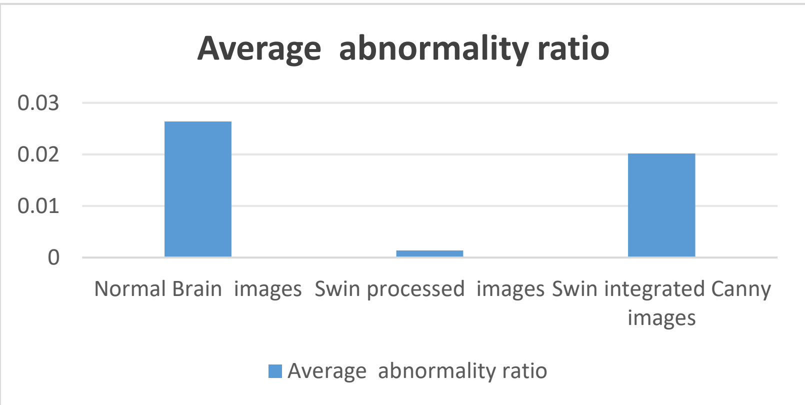
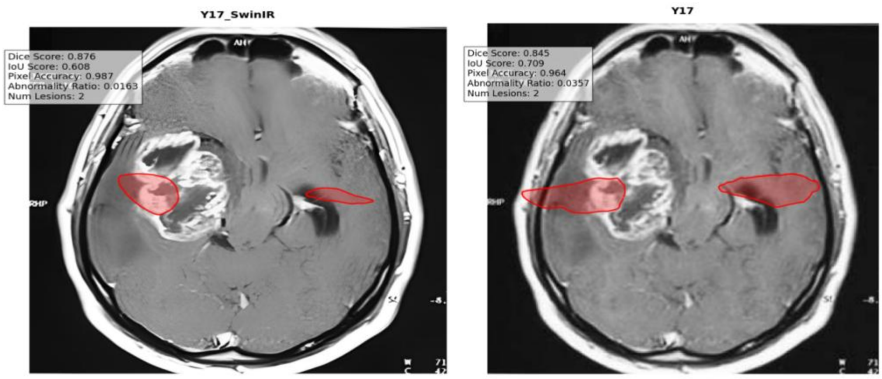


Figure 6: Average abnormality ratio comparison between three approaches

Swin processed images achieves high resolution which enhances the capability of contour algorithm as shown in Figure 7.Metric score for both processed and unprocessed image is depicted in figure.Our proposed framework elevates the performance of Original contour algorithm.



(a) (b)

Figure 7:Comparison of (a) Swin processed image (b)with unprocessed image

The performance of the original active contour algorithm is significantly enhanced through the preprocessing of images utilizing Swin-IR. As illustrated in the preceding figure, the effective identification of abnormal lesions improves markedly with increased image resolution, thereby ensuring that only the affected areas are distinctly projected. Ten brain tumour images have been employed to validate the efficacy of the proposed framework. Although the enhancement in accuracy is modest, it can be further augmented by increasing the number of images analyzed. The proposed framework optimizes the original active contour algorithm, yielding positive improvements across two critical metrics: Pixel Accuracy and Abnormality Ratio. This optimization not only underscores the robustness of the algorithm but also highlights its potential applicability across a broader spectrum of medical imaging scenarios.

Future work and Conclusion

In this research, we presented an integrated framework for early brain tumour detection by combining **SwinIR-based image enhancement**, **Canny edge detection**, and the **Active Contour (Snakes) algorithm**. The proposed method effectively improves the clarity and structural definition of brain images, enabling more accurate segmentation of tumour regions. By leveraging the SwinIR transformer architecture, the framework enhances low-resolution CT images to reveal finer details, which are crucial for identifying abnormalities. The improved image quality significantly boosts the performance of traditional segmentation techniques, as evidenced by the increase in **Pixel Accuracy** and a more precise **Abnormality Ratio**.

Experimental results on a subset of the **BraTS 2021 dataset** validate the effectiveness of the proposed approach, with SwinIR-preprocessed images achieving the highest average pixel accuracy of **97.12%**. Additionally, the framework successfully isolates affected regions more clearly than the standard active contour algorithm alone, highlighting its clinical potential for automated brain tumour analysis.

Although the proposed method demonstrates encouraging results, there are several avenues for further improvement and exploration:

1. **Larger Dataset Evaluation**: Future research will involve testing the framework on larger and more diverse datasets, including different imaging modalities such as MRI and PET scans, to assess generalization performance.
2. **Real-Time Implementation**: The current method relies on high-computation GPUs. Optimizing the model for real-time or edge deployment could enhance its usability in clinical environments.
3. **3D Image Segmentation**: Extending the framework to handle 3D volumetric brain scans can provide more comprehensive tumour localization across multiple slices.
4. **Hybrid Models**: Combining SwinIR with more advanced segmentation networks (e.g., U-Net, DeepLabV3+) could further boost accuracy and robustness.
5. **Clinical Integration**: Future work will also explore integration with electronic health record (EHR) systems and radiologist tools for assisted diagnosis and treatment planning.
6. **Explainability and Interpretability**: Enhancing the explainability of the segmentation output (e.g., using attention maps or saliency visualizations) could support medical professionals in trusting and adopting the system.

Funding statement:NA
Ethical Approval:NA
Consent to participate:Authordeclare their consent to participate.
Consent to Publish:Authordeclare their consent to publish.
Declaration of conflict of Interest :Authors declare no Conflict of Interest.
Data Availability statement:Dataset is freely available on public repository Kaggle.
Authors contribution:

Author	Contribution
Vertika Agarwal	Experimental resultand underlyingconcept
Shalini verma	Literaturereview
Geetanjali Tyagi	dataset preparation
Rupam Kumari	Overall structuring of paper and formatting

REFERENCES

[1] Sefti, R., Sbibih, D., & Jennane, R. (2025). An automatic B-snake model based on deep learning for medical image segmentation. Expert Systems with Applications, 270, 126481.
[2] Alsaif, H., Guesmi, R., Alshammari, B. M., Hamrouni, T., Guesmi, T., Alzamil, A., &Belguesmi, L. (2022). A novel data augmentation-based brain tumour detection using convolutional neural network. Applied sciences, 12(8), 3773.
[3] Ismaila, L. E., Rasti, P., Bernard, F., Labriffe, M., Menei, P., Minassian, A. T., ... &Lemée, J. M. (2022). Transfer learning from healthy to unhealthy patients for the automated classification of functional brain networks in fmri. Applied Sciences, 12(14), 6925.
[4]Rasheed, Z., Ma, Y. K., Ullah, I., Ghadi, Y. Y., Khan, M. Z., Khan, M. A., ... & Shehata, A. M. (2023). Brain tumour classification from MRI using image enhancement and convolutional neural network techniques. Brain Sciences, 13(9), 1320.
[5] Abdusalomov, A. B., Mukhiddinov, M., &Whangbo, T. K. (2023). Brain tumour detection based on deep learning approaches and magnetic resonance imaging. Cancers, 15(16), 4172.
[6] Stathopoulos, I., Serio, L., Karavasilis, E., Kouri, M. A., Velonakis, G., Kelekis, N., &Efstathopoulos, E. (2024). Evaluating Brain Tumour Detection with Deep Learning Convolutional Neural Networks Across Multiple MRI Modalities. Journal of Imaging, 10(12), 296.
[7]Li, Z., & Dib, O. (2024). Empowering Brain Tumour Diagnosis through Explainable Deep Learning. Machine Learning and Knowledge Extraction, 6(4), 2248-2281.
[8] Malla, P. P., Sahu, S., &Alutaibi, A. I. (2023). Classification of tumour in brain MR images using deep convolutional neural network and global average pooling. Processes, 11(3), 679.
[9] Almijalli, M., Almusayib, F. A., Albugami, G. F., Aloqalaa, Z., Altwijri, O., & Saad, A. S. (2025). Automatic Active Contour Algorithm for Detecting Early Brain Tumours in Comparison with AI Detection. Processes, 13(3), 867.
[10] Zahoor, M. M., Qureshi, S. A., Bibi, S., Khan, S. H., Khan, A., Ghafoor, U., & Bhutta, M. R. (2022). A new deep hybrid boosted and ensemble learning-based brain tumour analysis using MRI. Sensors, 22(7), 2726.
[11] Liu, J., Li, M., Wang, J., Wu, F., Liu, T., & Pan, Y. (2014). A survey of MRI-based brain tumour segmentation methods. Tsinghua science and technology, 19(6), 578-595.
[12] Sharma, H., &Bhadauria, H. S. (2017, September). An effective approach on brain tumour segmentation with polynomial hybrid technique. In 2017 3rd International Conference on Advances in Computing, Communication & Automation (ICACCA)(Fall) (pp. 1-8). IEEE.
[13] Megala, G., & Kumari, N. (2023, April). DeepGAN: an enhanced approach for detecting brain tumour. In 2023 Second International Conference on Electrical, Electronics, Information and Communication Technologies (ICEEICT) (pp. 01-06). IEEE.
[14] Biratu, E. S., Schwenker, F., Ayano, Y. M., & Debelee, T. G. (2021). A survey of brain tumour segmentation and classification algorithms. Journal of Imaging, 7(9), 179.
[15] Yang, T., Lu, X., Yang, L., Yang, M., Chen, J., & Zhao, H. (2025). Application of MRI image segmentation algorithm for brain tumours based on improved YOLO. Frontiers in Neuroscience, 18, 1510175.
[16] Shoaib, M. R., Zhao, J., Emara, H. M., Mubarak, A. S., Omer, O. A., Abd El-Samie, F. E., &Esmaiel, H. (2025). Improving brain tumour classification: an approach integrating pre-trained CNN models and machine learning algorithms. Heliyon, 11(10).
[17] Mishra, S., Sahu, P., & Senapati, M. R. (2019). MASCA–PSO based LLRBFNN model and improved fast and robust FCM algorithm for detection and classification of brain tumour from MR image. Evolutionary Intelligence, 12(4), 647-663.
[18] Hekmat, A., Zuping, Z., Bilal, O., & Khan, S. U. R. (2025). Differential evolution-driven optimized ensemble network for brain tumour detection. International Journal of Machine Learning and Cybernetics, 1-26.
[19] Irmak, E. (2021). Multi-classification of brain tumour MRI images using deep convolutional neural network with fully optimized framework. Iranian Journal of Science and Technology, Transactions of Electrical Engineering, 45(3), 1015-1036.
[20] Jabbar, A., Naseem, S., Mahmood, T., Saba, T., Alamri, F. S., & Rehman, A. (2023). Brain tumour detection and multi-grade segmentation through hybrid caps-VGGNet model. IEEE Access, 11, 72518-72536.
[21] Khushi, H. M. T., Masood, T., Jaffar, A., & Akram, S. (2024). A Novel Approach to Classify Brain Tumour with an Effective Transfer Learning based Deep Learning Model. Brazilian Archives of Biology and Technology, 67, e24231137.
[22] Muhammad, K., Khan, S., Del Ser, J., & De Albuquerque, V. H. C. (2020). Deep learning for multigrade brain tumour classification in smart healthcare systems: A prospective survey. IEEE Transactions on Neural Networks and Learning Systems, 32(2), 507-522.
[23] Khan, S. U. R., Zhao, M., & Li, Y. (2025). Detection of MRI brain tumour using residual skip block based modified MobileNet model. Cluster Computing, 28(4), 248.

[24] Ghosh, A., & Kole, A. L. O. K. (2021). A comparative study of enhanced machine learning algorithms for brain tumour detection and classification. Authorea Preprints.
[25] Patil, S., &Kirange, D. (2023). Ensemble of deep learning models for brain tumour detection. Procedia Computer Science, 218, 2468-2479.
[26]Liang, J., Cao, J., Sun, G., Zhang, K., Van Gool, L., & Timofte, R. (2021). Swinir: Image restoration using swin transformer. In Proceedings of the IEEE/CVF international conference on computer vision (pp. 1833-1844).
[27]Sekehravani, E. A., Babulak, E., & Masoodi, M. (2020).Implementing canny edge detection algorithm for noisy image. Bulletin of Electrical Engineering and Informatics, 9(4), 1404-1410.
[28]S. Verma, K. S. Kaswan and S. Kumar Bharti, "A Review of Machine Learning Techniques for Brain Cancer Diagnosis," 2024 4th International Conference on Advancement in Electronics & Communication Engineering (AECE), GHAZIABAD, India, 2024, pp. 915-921, doi: 10.1109/AECE62803.2024.10911825.