Research Article

A Robust Deep Learning Framework For Multi-Resolution Edge Detection in MR Images

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Abstract:

The analysis of anatomical structure and clinical decision-making depends on the accurate detection of edges of anatomical boundaries by using magnetic resonance (MR) imaging. Luckily, because of noise, low contrast, and inadequate multi-resolution representation in the image, traditional methods of edge detection and even deep learning-based traditional approaches have been unable to give satisfactory results. A multi-resolution deep learning approach is proposed for edge detection of anatomical structures using MR imaging. It will overcome the challenges posed by traditional edge detection methods and will focus on improving the edge-aware feature representation using transformers, edge attention, and multi-scale feature extraction. For efficient fusion of the spatial and semantic features and stabilization of the multi-level learning process, deep supervision and strengthened skip connections are introduced. In addition, in order to optimize the performance of pixels, boundaries, and structures simultaneously, a hybrid loss function is proposed. The proposed approach surpasses both the traditional approaches for edge detection and modern deep learning frameworks in respect to entropy, MSE, PSNR, SSIM, EKI, and FSIM metrics through extensive testing on MR image database. Therefore, the experimental results provide the accuracy of 96.7%, specificity of 95.8%, and F1 score of 95.3%, which is higher than the state-of-the-art methods that increase the effectiveness of the proposed deep learning technique.

Keywords: MR Images, Edge Detection, Multi-resolution, CNNs, Deep Learning.

1. Introduction

Edge detection is an integral component of medical image analysis, providing essential information for various image-processing tasks Proper detection of edges in Magnetic Resonance Images (MR) is an essential step that can help to establish boundaries between the tissues and diseases. Various challenges are experienced in medical imaging, which include noise, contrast, intensity non-uniformity, and edge issues, all of which are prevalent in MR images [1]. These factors adversely affect edge-detection performance. Some of the classical edge detection approaches that are filter-based and depend on the design of filters by hand based on gradients are the Sobel, Prewitt, Roberts, Laplacian of Gaussian, and Canny filters [2,3]. However, while those techniques are very effective regarding computation, they are highly sensitive to noise and parameter changes and cannot reveal multi-scale structures and semantic information.

Due to the low intensity of edges that may be broken apart and may exist in various tissues, their effectiveness may be compromised in the context of medical image processing [4]. In the last decade, medical image analysis has been greatly advanced owing to the developments in deep learning techniques and especially to techniques associated with convolutional neural networks [5]. The U-Net architecture and its modifications have proven to be highly effective architectures for biological image segmentation and feature extraction. However, there are several limitations present in the current multi-resolution U-Net-based architectures, including lack of ability to capture global dependencies within the context, inability to capture the boundaries of objects through feature extraction, and semantic differences between the representation of the encoder and decoder parts of the network, as well as inability to handle noisy MR images with structural variations [6,7]. To counter these problems, the research paper proposes multi-resolution deep learning U-Net architecture for performing edge detection in MR images.

In order to obtain better boundary-sensitive feature representation, the Deep learning framework adopts transformer-based global context representation, edge-aware attention-based approaches, and multi-scale feature extraction approaches through residual and dense encodings. In order to enhance the stability of multi-level learning and the effective fusion of spatial and semantic information, the Deep learning framework adopts deep supervision and enhanced skip connection approaches. In order to improve the accuracy, continuity, and consistency of the edge maps, a hybrid loss function is proposed by integrating multiple loss functions. Using a variety of quantitative evaluation metrics, the following contributions have been made in the current research work:

i. Proposing a multi-resolution deep learning architecture that uses transformer-based, multi-scale, and attention-based feature learning for edge detection problems.
ii. Mathematically defining the edge detection problem as a multi-level structural gradient optimisation problem.
iii. Experimentally showing the efficiency of the proposed approach compared to the best deep learning-based and traditional edge detection-based methods.

This proposed framework has tremendous potential to be used for advanced medical imaging problems and is a reliable and efficient framework to detect edges in MR images.

The research paper is divided into the following: The literature review is presented in section 2. The research methodology is presented in section 3. Experimental analysis of the results is presented in section 4. At last, section 5 summarises the conclusions.

2. Literature Review

Edge detector development has been an area of interest for many researchers. Relevant literature is as follows:

A. Conventional Techniques for Edge Detection

One significant area of interest in medical imaging and computer vision is edge detection. Gradient operators and second-order derivative operators like Sobel, Prewitt, Roberts, Log, and Canny are employed in edge detection techniques [8]. These techniques may be utilized for edge detection by identifying the abrupt variations in the intensity values of the images. These techniques are extremely sensitive to the parameters and the presence of noise [9]. However, these techniques are easy to implement and efficient in terms of computation. In addition, these techniques are not effective for complex medical images such as MR images due to the inability to process semantic and contextual information.

B. Multi-Scale Methods for Edge Detection

In an effort for dealing with the issues that arises in the application of those conventional techniques of edge detection, the multi-scale techniques were introduced [10]. The ability to carry out edge detection at multiple scales was made possible through the application of the wavelet transform, Gabor filters, and scale space. The application of these techniques helped to solve the problems encountered with the presence of noise as well as fine edges [11]. Even though these methods helped to avert the problems associated with the usage of the conventional methods, they still made usage of handcrafted features and predefined mathematical models, which restricted their flexibility and generalization potential for various MR imaging scenarios.

C. Edge Detection Using Deep Learning

The field of edge detection has undergone a major paradigm shift with the advent of deep learning approaches. Efficiency of convolution neural networks (CNN) in directly learning the hierarchical representation of features was seen [12]. Deep supervision was also incorporated with Holistically-Nested Edge Detection (HED) to enhance the edge detection capabilities of the networks. Further, with the capabilities of using multi-level features of CNN, edge detection was enhanced with the introduction of new models such as DexiNed, BDCN (Bi-Directional Cascade Network), and RCF (Richer Convolutional Features) [13]. Although the effectiveness of these models in edge detection of natural images was seen, the implementation of these models in medical imaging domain was difficult because of the features present**.**

D. U-Net and Its Diverse

The popularity of the U-Net framework can be attributed to its fact that the encoder-decoder architecture facilitates the incorporation of minimal spatial and high-level semantic information. In this regard, the U-Net framework has become a widely recognized model for biological image processing. For better feature representation and segmentation, several U-Net variants have been proposed, namely Dense U-Net, Res U-Net, Attention U-Net, and Multi-Resolution U-Net [14,15]. The Multi-Resolution U-Net is more appropriate of the complex medical imaging because it employs multi-scale convolutional filters to extract different scalable features [16]. Failure of U-Net-based models to perform optimally in boundary localisation is due to their design, which is mainly focused on segmentation.

E. Transformer-Based Models and Attention Mechanisms

In the improvement of the representation of medical image features, the latest studies on transformer models and attention mechanisms have been conducted. From the viewpoint of spatial attention and channel attention, the attention module in the Attention U-Net model highlights the important positions in the image [17]. From the viewpoint of the representation of local and global contexts, the hybrid CNN-Transformer model has shown good results [24]. However, the possibility of the explicit detection of edges in MRI images remains unknown, and most models have been developed for detection, segmentation and classification tasks.

Even though tremendous progress has been achieved in the field of edge detection of MR images, there are certain disadvantages associated with the existing approaches [18]. The conventional approaches are not robust to noise. The CNN-based approaches face difficulties in boundary continuity [19,20]. The semantic discrepancy between the encoders and decoders feature sets, as well as the absence of emphasis on learning edges, are the limitations of the multi-resolution U-Net-based approaches [21,22]. The approaches are successful in learning multi-scale features. The existing approaches are mainly focused on single-objective loss functions, which are unable to jointly optimize structural consistency, boundary accuracy, and pixel accuracy [23,24]. In light of the above-mentioned limitations, this research proposes an even more advanced multi-resolution deep learning UNet-based framework with better skip connections, global context using transformers, multi-scale feature extraction, edge-aware attention, and a hybrid structural gradient loss function. It is believed that this approach could offer an effective solution to precise edge detection in MR images, which would overcome the major limitations of existing approaches.

3. Proposed Methodology

The proposed methodology introduces a deep learning based multi-resolution framework for detecting edges from the medical MR images. The complete flow is as shown in Fig. 1

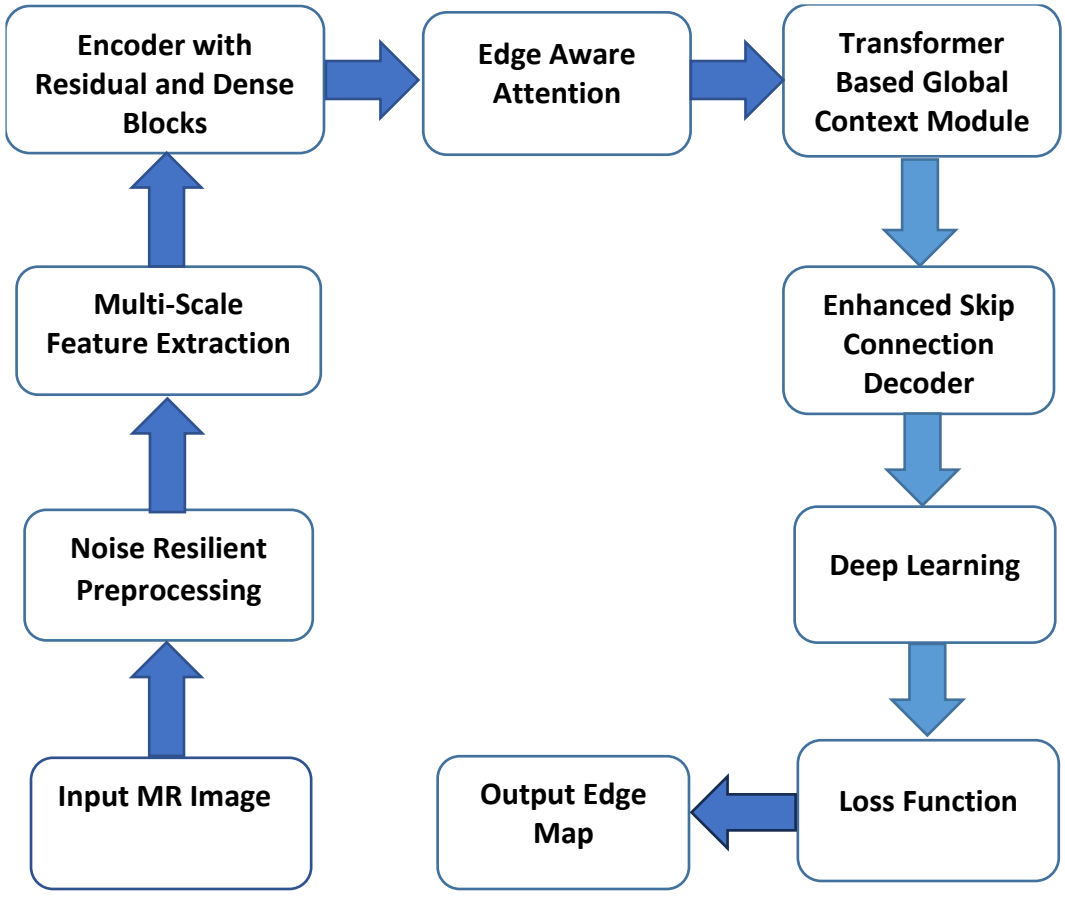


Fig. 1. Multi-resolution Deep Learning Framework

The MR images, which generally have low contrast, noisy, and intensity inhomogeneity characteristics, are used as input to the system. The edge detection process is challenging due to these characteristics, particularly for small body parts. Hence, to efficiently obtain the boundary information, advanced preprocessing and deep feature extraction techniques are necessary for the images. Let's represent the input MR image as:

$$I \in \mathbb{R}^{H \times W \times C} \quad (1)$$

Here, W, H and C denote the width, height and no of channels respectively.

The preprocessing module aims at preserving the structural details, enhancing the image's quality, and decreasing the noise level. For improving the local contrast and focusing the attention on poor edges, contrast-limited adaptive histogram equalisation (CLAHE) and bilateral filter to denoising the images are used. So, to increase the robustness of edge detection, this module ensures that the subsequent deep learning modules are fed with an enhanced and instructive image representation. The pre-processed image $\mathrm{I_p}$ which was obtained after applying an enhancement and denoising function:

$$\mathrm{I_p} = \mathcal{P}(\mathrm{I}) = \mathcal{E}(\mathcal{D}(\mathrm{I})) \quad (2)$$

Where,$\mathcal{D}(\cdot)$= Denoising operator and $\mathcal{E}(\cdot)$= Contrast enhancement operator

For feature extraction of the images at various scales in the spatial domain, the block of multi-scale feature extraction can employ dilated convolutional layers, feature pyramid networks (FPNs), and atrous spatial pyramid pooling (ASPP). By analysing the images from various receptive fields, the block of multi-scale feature extraction can effectively extract edge features from fine levels and structural features from coarse levels.

The detection of intricate boundaries in MR images involves the multi-scale representation as:

$$\mathrm{F_s^{(l)}} = \sigma\left(\mathrm{W_s^{(l)}} *_{\mathrm{r_s}} \mathrm{I_p} + \mathrm{b_s^{(l)}}\right) \quad (3)$$

Where,l= layer index,$\mathrm{r_s}$= dilation rate,$*_{\mathrm{r_s}}$= dilated convolution,$\sigma(\cdot)$= activation function (ReLU),$\mathrm{W_s^{(l)}}$, $\mathrm{b_s^{(l)}}$= learnable parameters.

The combined multi-scale features can be represented as:

$$F_{ms} = \bigoplus_{s=1}^{S} F_s^{(l)} \quad (4)$$

Where, $\bigoplus$ denotes concatenation.

The encoder network is built using residual and dense blocks to improve hierarchical feature learning and information transfer across layers. Dense connections help with feature reuse and representation learning, while residual connections solve the problem of gradient degradation during training. This module preserves the spatial information required for edge detection and extracts deep semantic features. Within a residual block

$$F_{res}^{(l)} = F_{ms}^{(l)} + \mathcal{F}(F_{ms}^{(l)}, W^{(l)}) \quad (5)$$

Where, $\mathcal{F}$ denotes convolutional transformation.

Every layer in the dense block uses feature maps from all previous layers. The dense block output is

$$F_{dense}^{(l)} = H_l\left([F_{dense}^{(0)}, F_{dense}^{(1)}, \dots, F_{dense}^{(l-1)}]\right) \quad (6)$$

Where, $[.]$ represents concatenation and $H_l(\cdot)$ is the compound function of convolution, activation and normalization.

With the reduction of unnecessary background responses and the focus on edge information, the edge-aware attention module improves feature maps with boundary awareness. To improve feature maps, methods such as squeeze-and-excitation (SE), edge attention modules (EAM), and convolutional block attention modules (CBAM) are used. This block greatly improves the discriminability of weak and subtle edges in MR images. The channel attention (A_c), spatial attention (A_s), and edge refined features (F_{att}) are as follows:

$$A_c = \sigma(W_2 \cdot \delta(W_1 \cdot \mathrm{GAP}(F_{dense}))) \quad (7)$$

$$A_s = \sigma(f^{7\times7}([AvgPool(F_{dense}); MaxPool(F_{dense})])) \quad (8)$$

$$F_{att} = A_c \otimes A_s \otimes F_{dense} \quad (9)$$

Where, $\otimes$denotes element-wise multiplication.

For modelling the global contextual relationships and dependencies in the image, a transformer module is added at the bottleneck layer. The transformer module helps in capturing the global structural information, whereas the conventional convolutional layers capture only the local information. In the distant regions of the image, the transformer module improves the structural consistency and edge continuity.

Given flattened feature tokens $X \in \mathbb{R}^{N\times d}$:

$$Q = XW_Q, K = XW_K, V = XW_V \quad (10)$$

Self-attention is given by:

$$\mathrm{Att}(Q,K,V) = \mathrm{softmax}\left(\frac{QK^T}{\sqrt{d}}\right)V \quad (11)$$

Output feature denoted by:

$$F_{tr} = \mathrm{Att}(Q,K,V)W_O \quad (12)$$

From a low-resolution representation of input data, the decoder generates high-resolution representation of the said data. This process involves a low-resolution representation that is generated first; then a high-resolution input data is generated by up-sampling the feature representations. The decoder uses enhanced skip connections to combine the lower spatial resolution of the encoder and the higher-level semantic space of the encoder's deeper layers. Fusing the decoder and encoder representations in a semantic manner reduces the difference between them and reconstruct more accurate and fine edges. Encoder features $F_e^{(l)}$ and decoder features $F_d^{(l)}$ are fused as:

$$F_{skip}^{(l)} = \phi\left(F_e^{(l)} \oplus F_d^{(l)}\right) \quad (13)$$

Where, $\phi(\cdot)$ denotes attention-guided fusion.

Decoder output at level l is given as:

$$F_{dec}^{(l)} = \sigma\left(W_d^{(l)} * \mathrm{Up}(F_{dec}^{(l+1)}) + b_d^{(l)}\right) \quad (14)$$

Where, $\mathrm{Up}(\cdot)$ denotes up-sampling.

The addition of auxiliary output layers and matching loss functions allows for the implementation of deep supervision at various decoder levels. This method facilitates multi-level feature learning and enhances gradient propagation. Deep supervision improves convergence stability at various resolution levels and fortifies edge representation by imposing learning at intermediate layers. Mid-range predictions:

$$\hat{Y}^{(l)} = \psi(F_{dec}^{(l)}) \quad (15)$$

Total supervised loss is denoted by:

$$\mathcal{L}_{ds} = \sum_{l=1}^{L} \lambda_l \, \mathcal{L}(\hat{Y}^{(l)}, Y) \quad (16)$$

Where, Y is the ground truth edge map.

The performance evaluation metrics defined for assessing the edge detection closely match the optimisation objective of the suggested multi-resolution U-Net model. Binary cross-entropy (BCE), edge-aware loss (Edge), dice loss (Dice), and structural similarity (SSIM) loss are combined to create a hybrid loss function. Commonly used quantitative measures like accuracy, sensitivity, specificity, Dice similarity coefficient, and precision are directly correlated with these losses. In order to optimize the network's performance:

$$\mathcal{L}_{BCE} = -\frac{1}{N}\sum_{i=1}^{N}[y_i log(\hat{y}_i) + (1 - y_i) log(1 - \hat{y}_i)] \quad (17)$$

$$\mathcal{L}_{Dice} = 1 - \frac{2\sum_i y_i \hat{y}_i}{\sum_i y_i + \sum_i \hat{y}_i} \quad (18)$$

$$\mathcal{L}_{Edge} = \left\| \nabla Y - \nabla \hat{Y} \right\|^2 \quad (19)$$

$$\mathcal{L}_{SSIM} = 1 - \mathrm{SSIM}(Y, \hat{Y}) \quad (20)$$

$$\mathcal{L}_{total} = \alpha \mathcal{L}_{BCE} + \beta \mathcal{L}_{Dice} + \gamma \mathcal{L}_{Edge} + \delta \mathcal{L}_{SSIM} \quad (21)$$

This combined loss function ensures the model has strength in terms of structural integrity, resistance to class imbalance, and accurate border localization. This is a requirement for improving the overall efficiency of edge detection. The final outcome of the model proposed is the precise edge map for the MR image, which depicts anatomical boundaries with high accuracy and continuity. The proposed model has the ability to detect edges that are subtle and complex compared to the variant of the U-Net models. The obtained edge map is as follows:

$$\hat{Y} = \sigma(F_{dec}^{(0)}) \quad (22)$$

4. Experiment Results and Analysis

The edge detection approach that is proposed will be trained on the MR images in the Kaggle LGG [25] datasets. This Kaggle LGG MRI dataset is a large-scale annotated brain MRI dataset which has segmentations masks. Hence, this dataset is very appropriate for purposes such as edge detection and tumor boundaries using deep learning-based systems. The dataset was randomly divided into 70% training, 20% validation, and 10% testing sets in this research paper. The volumetric images are transformed into slices of 2D images and then pre-processed prior to being used as the input data for training the proposed model. All of the aspects associated with training, testing, and data manipulation were carried out through the python programming language. The experiments are performed using a computer with 16 GB of RAM and an NVIDIA GPU with RTX 600. The average time required for training each epoch is about 1.5 minutes and the total training process was accomplished in 2.5 hours. Sigmoid activation function and the probability of dropout = 0.5 have been used in the experiment. For the purpose of validating the model, k-fold validation, k=5 is applied. The output edge map of the input MR images of the suggested framework is displayed in the Fig. 2.

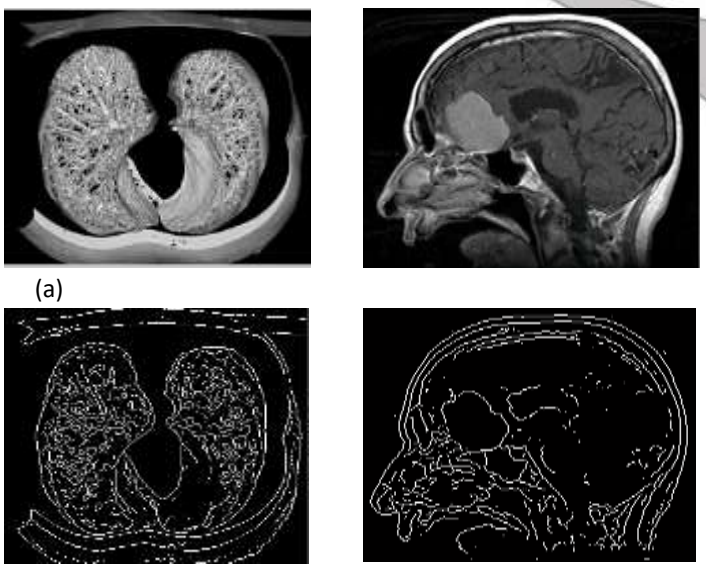


Fig.2. (a) Input MR Image (b) Output Edge Map generated by the Proposed Framework

The quantitative criteria for performance evaluation can be utilised to assess the efficiency of the suggested method in the context of accuracy, recall, specificity, precision and F1 score. This evaluation is conducted on the basis of a confusion matrix containing True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). The following are the measures of evaluation:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (23)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (24)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (25)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (26)$$

$$\text{F1 Score} = \frac{2X\ Precision\ X\ Recall}{Precision+Recall} \quad (27)$$

An improved F1 score indicates better classification performance by the evaluated model. It is observed that a higher level of specificity means that the model is able to deal with negative cases, as well as for minimizing false alarms. Recall can perform a significant role in preventing cases of anomalies or misleading representations. A higher level of specificity aims to prevent false alarms. The improved values for key parts of the segmentation process, along with the excellent accuracy in detecting new cases of abnormalities, are also important. Table 1 and Fig. 3 shows the comparison of performance for different methods of edge detectors.

Table 1: Metrics for Performance Evaluation of Edge Detection Method

Method	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	Specificity (%)
Canny	83.5	81.7	83.6	82.6	83.4
HED	89.1	89.0	90.5	89.7	91.8
U-Net	91.7	90.8	90.4	90.6	93.5
MR U-Net	93.5	94.1	94.4	94.2	94.6
Proposed	96.7	94.9	95.8	95.3	95.8

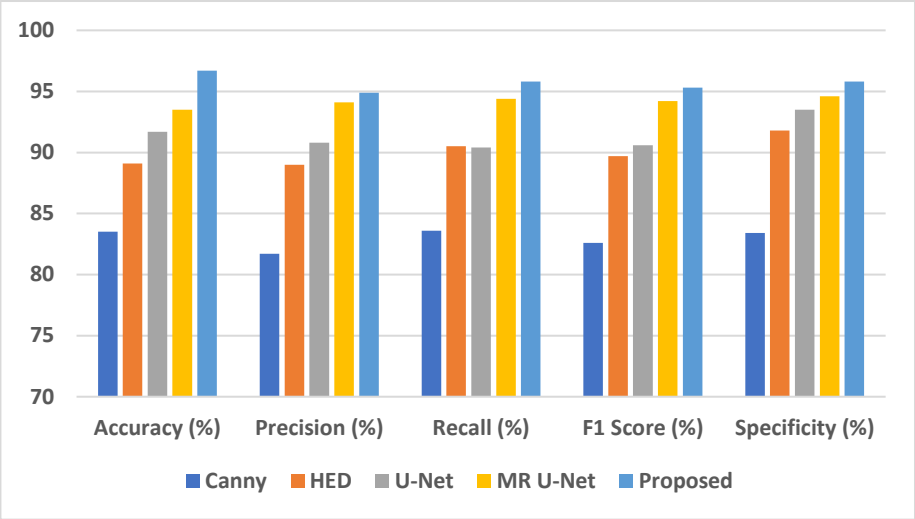


Fig.3 Graphical Performance Evaluation of Edge Detection Methods

The comparison highlights the limitations of conventional edge detection techniques, such as Sobel, Prewitt, Canny, and Laplacian, in accurately detecting complex and subtle boundaries in medical images. These methods primarily rely on low-level gradient and intensity variations, limiting their ability to capture intricate structural details and multi-scale features. In contrast, deep learning-based approaches, particularly U-Net variants, demonstrate improved performance across the evaluated metrics by leveraging hierarchical feature extraction and data-driven learning. The proposed robust deep learning framework achieves superior overall performance compared with conventional edge detection methods and existing deep learning approaches, demonstrating its effectiveness in detecting complex and fine-grained edges in MR images.

The loss function used to evaluate the performance of the edge detector that fits well with the optimization goal of the proposed multi-resolution U-Net model. Commonly reported measures directly relate to the chosen combination of Binary Cross-Entropy and Dice loss. A weighted mix of edge-aware, Dice, binary cross-entropy, and structural similarity losses forms the overall loss function. The selected weighting coefficients are α=0.4, β=0.3, γ=0.2, and δ=0.1. This setup ensures fair optimization of border precision, region overlap, pixel-level accuracy, and structural consistency. The weights are adjusted to ensure that $\alpha + \beta + \gamma + \delta = 1$. Also, to improve multi-scale learning stability and convergence, exponentially decaying weights are used along with deep supervision throughout the decoder layers.Fig.4 shows the curve of the loss function of the proposed framework.

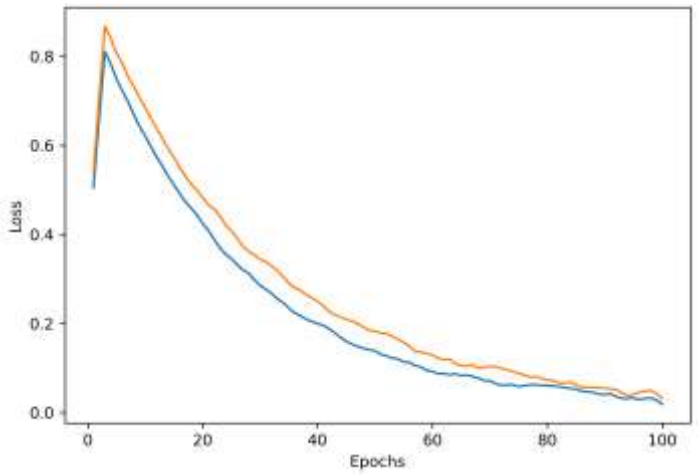


Fig. 4. Curve of the Loss Function

The training and validation loss curve for the suggested robust deep learning framework shows consistent and robust convergence. At the beginning, the loss converges quickly, which shows effective learning of multi-scale

edge features. Both curves remain stable with less oscillation as training proceeds, which shows robustness and no overfitting. The ability of the proposed framework for MR image edge detection is also shown by the good match between the loss of training and validation.

Multiple objective image quality and edge preservation measures like entropy, mean squared error (MSE), peak signal to noise ratio (PSNR), structural similarity index (SSIM), edge keeping index (EKI), and feature similarity index (FSIM) are employed in Table 2 and graphical representation is shown in the Fig.5 to compare the proposed robust deep learning method with traditional edge detection techniques and multi resolution U-Net based approaches. The texture complexity and richness of edge information in the identified edge maps are measured in terms of entropy. Higher entropy values represent better preservation of structural details. Lower values represent better reconstruction capability. MSE measures the pixel-wise error difference between the reference and the detected edge MR image.

Table 2: Quantitative Comparison of Edge Detection Method

Method	Entropy	MSE	PSNR (dB)	SSIM	EKI	FSIM
Canny	5.55	0.0166	29.21	0.772	0.707	0.741
HED	5.99	0.0122	31.84	0.830	0.786	0.808
U-Net	5.81	0.0095	33.68	0.821	0.785	0.799
MR U-Net	6.14	0.0074	35.55	0.849	0.819	0.830
Proposed	6.51	0.0044	37.28	0.909	0.846	0.865

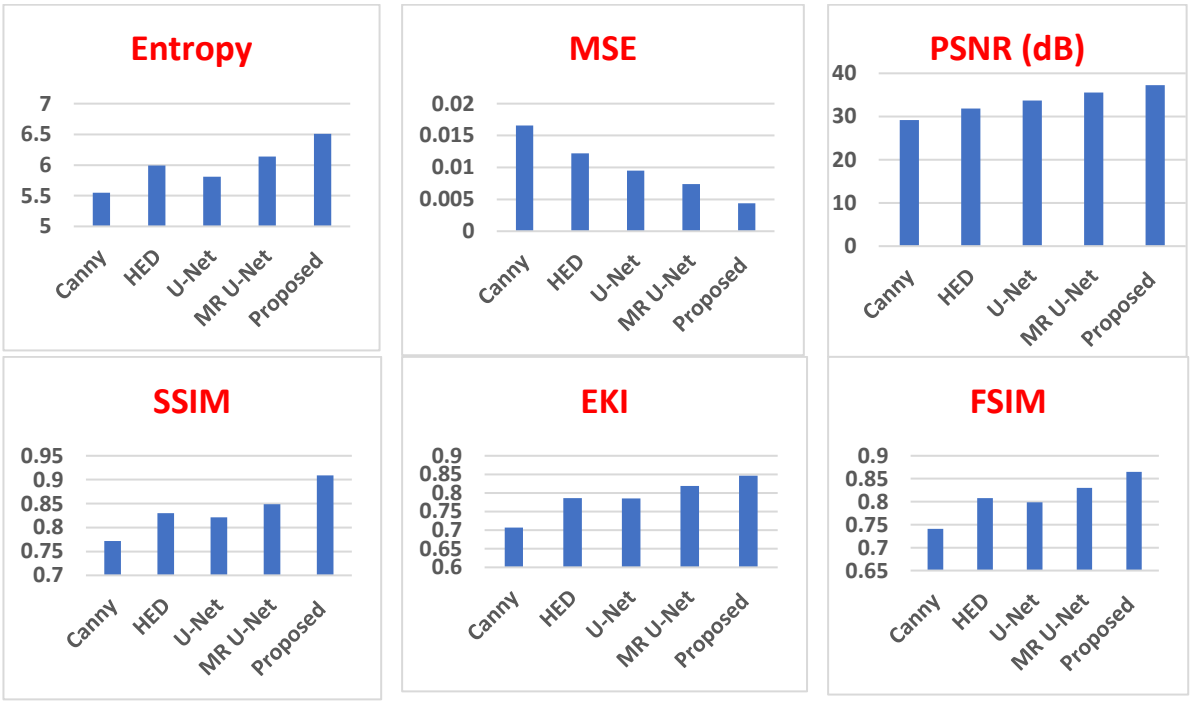


Fig. 5. Graphical Quantitative Comparisons of Edge Detection Method

The greater the PSNR value, the less distortion and better edge quality. PSNR measures the signal fidelity of the detected edges. SSIM measures the structural similarity between the detected edges and ground truth by capturing structural information, contrast, and brightness. EKI is especially important in the assessment of edge detection algorithms for medical images because it measures the algorithm's capability to maintain the continuity and sharpness of edges. FSIM measures the similarity between images by combining phase congruency and gradient magnitude and offers a good measure of consistency at a feature level. From the discussion, the traditional approaches like Sobel, Prewitt, Roberts, Laplacian, and Canny operators perform moderately because they use gradient operators created by human designers and do not possess the capability to describe edge information at multiple scales.

By learning hierarchical representations of features, deep learning-based approaches, such as HED and the traditional U-Net, have shown improved performance. Nevertheless, based on all parameters, the best-performing model is the proposed deep learning Multi-Resolution U-Net model, which clearly demonstrates its

superior capability of preserving fine anatomical boundaries and detecting strong multi-scale edge features from MR images. The above experimental results have confirmed that the fusion of deep feature learning and multi-resolution feature fusion is a powerful approach for performance improvement of the edge detector, and thus the proposed model is the most suitable one for precise and trustworthy MR image analysis.

5. Conclusions

This research work focused on a robust multi-resolution deep learning framework for precise deep feature-driven edge detection in MR images. The proposed framework efficiently extracts the fine and coarse details of complex medical MR images by utilizing a multi-scale feature extraction method, a hybrid loss function, and an advanced skip connection approach. The experimental results demonstrate that the method proposed outperforms the most advanced deep learning techniques currently being used and conventional edge detection techniques in terms of 96.7% accuracy, 94.9% precision, 95.8% recall, 95.8% specificity, and 95.3 % F1 score. The experimental analysis conducted using different objective measures like entropy, MSE, PSNR, SSIM, EKI, and FSIM reveals that proposed framework performs better than the baseline deep learning models and conventional edge detection approaches. With the higher entropy, PSNR, SSIM, EKI, and FSIM values and significantly lower MSE, the results indicate improved edge preservation, accuracy, and perceptual structural fidelity. With little overfitting and optimal optimisation convergence, the convergence behaviour of the loss curves also shows the robustness, efficiency, and generalisability of the proposed framework. Edge localisation in difficult MR image regions is improved by the multi-resolution approach, which helps the model to maintain spatial information while improving semantic information. In addition, the hybrid loss function, which seeks to maximise structural similarity and pixel accuracy at the same time, also helps to improve edge detection and provides a reliable and effective approach for edge detection in MR images. In addition, the suggested framework has a very high potential to be integrated into an advanced medical image analysis system, including but not limited to segmentation, diagnosis, and computer-aided detection.

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