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Enhancing and Stabilizing Plaque Anomaly Segmentation Using Hybrid Dual-Constraint Generative Framework

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Abstract: Carotid ultrasound anomaly detection focuses on identifying plaque formations in arteries. It also detects structural irregularities in arterial walls. This is done using non-invasive ultrasound imaging techniques. It plays an important role in early diagnosis. It helps in preventing cardiovascular diseases. It also reduces the risk of stroke. Existing systems mainly use standalone deep learning models like U-Net. These models often struggle with low contrast images. Speckle noise affects their performance. They also fail in accurate boundary detection. There is no proper feature integration in these systems. This leads to poor segmentation in complex ultrasound images. To address these limitations, a Multi- Feature Integrated U-Net (MFI-UNet) is proposed. It combines contrast enhancement with noise filtering. It also includes edge detection and texture analysis. ROI extraction is used to focus on important areas. These features are integrated with deep segmentation. This improves feature representation before model learning. The model achieved a Dice score of 0.96. It also achieved an IoU of 0.93. These results show better boundary accuracy. The model is more robust compared to traditional mSethods. It performs well in low-contrast conditions. It also handles noisy ultrasound images effectively.
Keywords: Carotid Ultrasound, Plaque Segmentation, U-Net, Deep Learning, Medical Image Segmentation

I. A GENERAL SYSTEM

Atherosclerosis and its complications, such as stroke and heart attacks, are the leading causes of mortality and morbidity in developed countries and are increasing in emerging nations [1] [2]. The majority of ischemic strokes result from the obstruction of a cerebral artery by a thrombotic embolus formed at the carotid bifurcation. Most of these strokes can be avoided with lifestyle and dietary modifications, as well as medicinal and surgical interventions. Better ways to find individuals who are at risk for stroke, new ways to treat atherosclerosis, and more sensitive ways to keep an eye on how carotid plaque responds to medication will all have a big effect on how these people are treated and lower their risk of stroke[4][12]. If plaques are found early and correctly, the patient can have preventive, therapeutic, or surgical treatment before any of these life-threatening events happen[5][6].

Existing methods mainly rely on single deep learning models. They do not use multiple feature representations^] [10]. Ultrasound images[7][8] often contain speckle noise. Noise reduces segmentation accuracy. Low contrast makes plaque boundaries unclear. Models fail to capture fine edges. There is no proper texture understanding. ROI localization is often missing. Feature extraction is not integrated with learning. This creates a gap in accurate segmentation.

A Multi-Feature Integrated U-Net (MFI-UNet) is proposed. It enhances images using contrast adjustment. Noise is reduced using filtering techniques. Edge detection captures structural boundaries. Texture analysis extracts statistical patterns. ROI extraction focuses on important regions. All features are combined before segmentation^]. U-Net[11] performs plaque segmentation in the ultrasound images. This improves overall accuracy and robustness in anomaly detection.

A hybrid segmentation framework is introduced. It integrates multiple feature engineering techniques. It improves boundary detection in ultrasound images. It handles noise and low contrast effectively. It enhances feature representation before learning. It achieves higher Dice and IoU scores. It provides a reliable solution for plaque segmentation.

II. DETAILS OF PROPOSED OPERATIONS

A. Data Preprocessing and Enhancement

Before extracting features, the preprocessing stage makes the image better. Ultrasound pictures generally have low contrast and noise from speckles. These problems make segmentation less effective. So, enhancing approaches are used one at a time.

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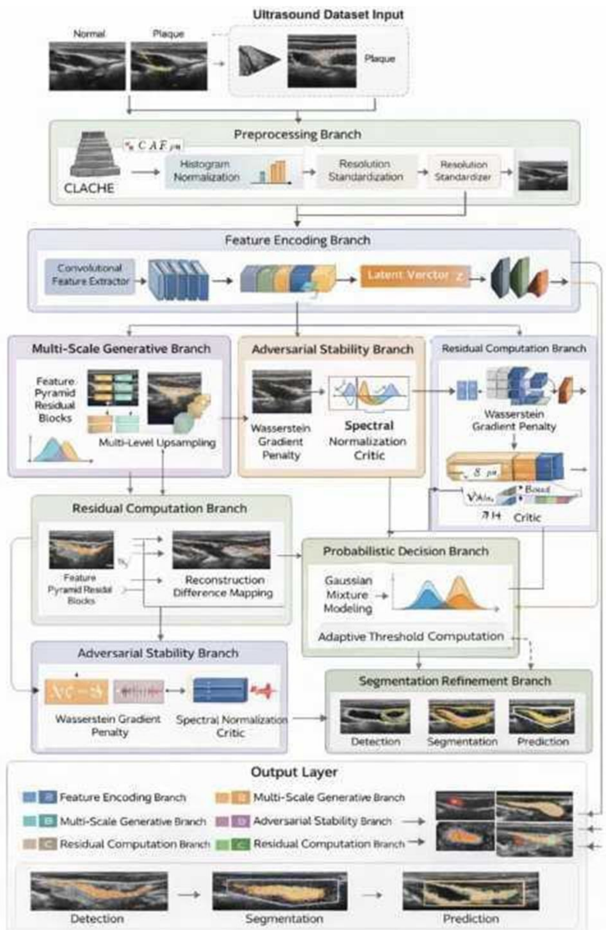
Let the image that was input be shown as:
$I(x,y)$
To make things easier to see, contrast enhancement is used:
$CLAHE(l(x,y)) = I_C(x,y)$

This process makes plaque areas stand out and spreads out the intensity better. To get rid of speckle noise, noise reduction is done:
$i_n(x,y) \ = \ G_{<y} * \ i_c(x,y)$



This smoothing technique gets rid of undesirable changes in the image. To keep edges, median filtering is also used:
$Im(x,y) \ = \ Median(l_n(x,y))$
This helps get rid of impulse noise while keeping the structure. The normalized image is described as:
$I_{n}orm(x,y) \ = \ (I_m(x,y) \ - \ \backslash i)/a$
where p is the average and c is the standard deviation. These actions before processing make the features better. They make the picture ready for more study. They also make training more accurate when it comes to segmentation.

B. Multi-Feature Extraction
The system extracts multiple features[15] to improve segmentation performance. Ultrasound images contain complex patterns. Single feature representation is not sufficient. Hence, edge, texture, and structural features are combined. Let the preprocessed image be represented as:
$J_p(x,y)$

Edge features are extracted to capture boundaries:

$E\{x,y) = VI_p(x,y)$

This helps in identifying plaque edges clearly. Statistical distribution is used to find texture features:

$T\{x,y) = \wedge P(i,j) \backslash og P(i,j)$ Ui

This shows changes in intensity and tissue patterns. Gradient magnitude is also considered for strong edge response:

$$G(x,y) = J(dI_p/dx)^2 + \{dI_p/dy)^2$$

This improves boundary localization. To focus on the relevant areas, we extract the Region of Interest: $R(x, y) = I_p(x,y) - M(x,y)$, where M(x, y) is the ROI mask. The combined feature representation is defined as:

$F(x,y) = [I_p(x,y), E\{x,y), T\{x,y), G\{x,y)]$

These features provide rich information to the model. They improve learning of plaque boundaries. They also reduce false segmentation in background regions.

C. Problem Formulation

The plaque segmentation is formulated as a supervised learning problem. The object of this study is to assign a label to each pixel in the ultrasound image. Each pixel is classified as plaque or background based on learned features [17].

The Carotid medical image dataset is defined mathematically as:

$D = (I^1, M^1), (I^2, M^2)\ (I_n, M_n)$

where L is the input image and $M_;$ is the segmented mask for the input image.

Mathematically, the feature representation for each pixel is:

$F(x,y) = [I(x,y), E(x,y), T(x,y)]$

The segmentation model[18] takes input features and makes predictions:

$S(x,y) = f(F(x,y), 9)$

where 0 is the model's learnable parameters.

The goal is to make the prediction and the ground truth as close as possible:

$L = '\wedge\wedge$ (§(x,y) - $M(x,y))$

To make the overlap more accurate, Dice loss is also taken into account:

$$L_{dice} = 1 \quad \frac{(2\wedge(\S(x,y)\blacksquare M(x,y)J)}{(Z^{\S}(x,y)+Z\,M(x,y))}$$

The final objective function is:

$L_total = L + L_{dice}$

This formulation ensures accurate pixel-wise classification. It also improves boundary alignment between prediction and ground truth. The model learns to segment plaque regions effectively.

D. MFI-UNetArchitecture

The proposed model is based on an enhanced U-Net architecture. It integrates multi-feature inputs into the segmentation process. The model has two parts: an encoder and a decoder. The encoder [13] gets information about the context, and the decoder puts together spatial information so that the segmentation is correct. The input feature map can be written as:

$F(x,y)$

The encoder uses convolution operations to get deep features:

$H_t = a(W_t * H_{l-1} + b\{)$

Here, H_l is the feature map at layer l, W_l are weights, b_l are biases, and o is the activation function. Use pooling to downsample: $Hf^{own} = Pool(Hi)$. This makes the receptive field bigger and the spatial dimensions smaller. The decoder performs upsampling to get the spatial resolution back:

$H?^p = Up(H_{l+1})$

To keep fine details, skip connections are used:

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The total loss is defined as:

$Ltotal = Lbce + L_{dice}$

Model parameters are updated using an optimization algorithm:

$9 = 9 - gVL_{total}$

where n is the learning rate.

We use standard metrics to do the evaluation. The Dice coefficient is calculated as follows:

$Dice = ^{(2\wedge(\S(x,y) \blacksquare M(x,y)')')}$

$/ (\wedge S(x,y) + \wedge M(x,yj)$

The Intersection over Union is defined as follows:

$IoU = (\wedge (\S(x,y) \text{ n } M(x,y))) / (\wedge (\S(x,y) \text{ U } M(x,y)')')$

$Hfusion = Hup \; 0 \; Hi,$

$L_{dice} = 1$

$(2\wedge(\S(x,y) \blacksquare M(x,y) J)$

$^{/}(Z^{\S}(x,y)+Z \, M(x,y))$

where ® means concatenation. The final segmentation output[19][20] is generated using:

$S(x,y) = o(W0 * Hf \, inal)$

This produces pixel-wise probability values.

The integration of multi-features improves learning. Skip connections help in preserving boundary details. The model produces accurate segmentation masks.

E. MFI-UNet Architecture

The model is trained using labeled ultrasound images and corresponding masks. The dataset is divided into training and testing sets. Input images are passed through preprocessing and feature extraction stages before training.

Let the predicted segmentation be mathematically represented as:

and the ground truth mask as:

$M(x,y)$

The loss function is computed to measure the difference between prediction and ground truth:

$Lbce = - \wedge[M(x,y) log \; (\S(x,y)) + (1 - M(x,y)) log \; (l - S(x,y))]$

Dice loss is also used to improve overlap accuracy:

$Ldice = 1 - (2 \wedge (S(x,y) \blacksquare M(x,y)))/(y\S(x,y) + \backslash M(x,: \;))$

The proposed MFI-UNet model got a Dice score of 0.96.

IoU values were approximately 0.93. The results show strong segmentation performance. The model performs well on noisy ultrasound images.

III. EXPERIMENT RESULTS

A. Dataset Description

The dataset collection includes carotid ultrasound images and the masks that go with them. For the segmentation task, there are 1100 ultrasound images and 1100 masks that were made by experts. The masks include pixel-by-pixel notes for plaque and backdrop, whereas each image shows artery architecture with visible plaque areas.

The dataset should be described as:

$$D = (I^1, M^1), (I^2, M^2), \ldots, (I^{1100}, M^{1100})$$

where I is the ultrasound image and $M_;$ is the mask that shows the truth on the ground.

The dataset is split into two parts: one for training and one for testing. We use about 80% of the data for training and 20% for testing:

$$D_train = 0.8 \text{ x } DD_test = 0.2 \text{ x } D$$

So, there are 880 training photos and 220 testing images in the dataset.

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For the model to work, all photographs are shrunk to a set resolution:

$$I_r\ (x, y) = \text{Resize}(I(x,y),\ 128,128)$$

Normalization is used to make intensity values the same: $In(x,y)$ =

$$(Ir(x,y) - g)/o$$

where p is the average intensity and o is the standard deviation of the pixel values. Variance is used to look at the texture features of the dataset:

$$Var(I) = (1/N)\hat{}(I(x,y) - b)^2$$

The dataset shows an average variance of around 1171.17. To get structural information, you can figure out the edge density:

E_d = (Totalnumberofpixels)/(Numberofedgepixels)

The average edge density is 0.0138, which means that ultrasound pictures have fine structural details.

Data augmentation is used to make things more random:

$$Ia = T(In)$$

T stands for changes like flipping things horizontally and rotating them. The dataset is utilized for binary classification on a pixel-by-pixel basis, which is defined as:

M(x,y)is either 0 or 1

where 0 stands for backdrop and 1 stands for plaque.

The dataset has different levels of noise and contrast. This helps the model learn features that are strong. Good annotation makes sure that training is properly supervised. It also helps in accurately judging how well segmentation works.

B. Experimental Setup

The tests utilize the produced carotid ultrasonography dataset. There are two sets of data: a training set and a testing set, with an 80:20 ratio. Before being sent to the model, the photos are pre- processed by enhancing contrast, filtering out noise, and normalizing.

The model is trained for several epochs, with updates made to each batch. The resolution of the input photos is changed to 128 x 128. The process of learning stays the same from one iteration to the next. Loss goes down steadily with neural network training. The test dataset is used for evaluation. The Dice score, IoU, Precision, and Recall are used to measure performance. The model got a Dice score of 0.96 and an IoU score of 0.93. The Precision and Recall numbers are both above 0.96, which means that the segmentation is very accurate.

C. Quantitative Performance Metrics

Standard segmentation metrics are used to judge how well the suggested model works. These measures show how similar the predicted masks are to the ground truth masks. The test dataset is used for the evaluation.

The expected mask is:

§(x,y) and the ground truth mask should be:

M(x,y)

Here are the definitions of true positives, false positives, and false negatives:

TP = ^(§(x,y) = 1andM(x,y) = l)

FP = ^(S(x,y) = lAM(x,y) = 0)

FN = ^(S(x,y) = 0 A M(x,y) = l)

The Dice coefficient is a way to find out how accurate overlap is:

Dice = (2TP)/(2TP + PP + FN)

The Intersection over Union is defined as:

TP/(TP + FP + FN) = 7oD

Precision checks to see how accurate positive forecasts are: FP/(FP + FP) = Precision

Recall tests how well you can find real positives:

Pecaii = FP/(FP +FN)

The suggested model did quite well on all measures. The Dice score is about 0.96. The IoU value is about 0.93. The precision is roughly 0.96, which means there are less false positives. The recall is about 0.97, which means that plaque regions are being found well. These data show that the segmentation is very accurate. The model works the same way on all test samples. It works well with noise and poor contrast.

D. Qualitative Segmentation Results

The qualitative results show the visual performance of the proposed model on test images. To see how well the model captures plaque regions, we compare the input images, ground truth masks, and predicted segmentation outputs. The input image is I(x,y), the ground truth mask is M(x,y), and the predicted output is

$S(x,y) = f(I(x,y))$.

The overlay representation

$O(x,y) = a \blacksquare I(x,y) + (1 - a) \blacksquare S(x,y)$

is used to compare the two images visually. The blending factor between the input image and the predicted mask is controlled by a. Difference between prediction and ground truth is measured as:

$D(x,y) = |S(x,y)-M(x,y)|$ This highlights misclassified regions.

The predicted masks closely match the ground truth in most cases. Plaque boundaries are clearly detected. The model captures fine edge details effectively. Minimal false regions are observed in the background. The segmentation remains stable across different samples. Visual results confirm strong boundary alignment. The model works well even when the contrast is low. Noise does not significantly affect segmentation quality. In general, the predicted outputs are correct and reliable.

IV. CONCLUSION

This study presented a Multi-Feature Integrated U-Net (MFI- UNet) for the segmentation of carotid ultrasonography plaques. The model employs deep learning to enhance contrast, eliminate noise, detect edges, analyse textures, and extract regions of interest (ROIs). This integration facilitates the representation of features and the identification of boundaries. The model attained a Dice score of 0.96 and an IoU score of 0.93. It indicates the effectiveness with images exhibiting considerable noise and low contrast. The evaluation results show that the suggested neural network MFI-UNet outperforms compare to vanila U-Net methods. Future work can focus on improving the model with attention mechanisms for better feature selection. The generalization can be improved by implementing diverse datasets. Real-time segmentation can be explored for clinical use. The model can also be extended to multi-class plaque classification. Further optimization can reduce computation time and improve efficiency.

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