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A Hybrid Model for the Segmentation of Mammogram Images using Otsu Thresholding, Morphology and U-Net

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Mammogram image segmentation is crucial for early detection and treatment of breast cancer. Timely detection can help in saving the patient's life. By accurately identifying and isolating regions of interest in mammograms, we can improve diagnostic accuracy. In this paper a hybrid model for segmentation using Ostu thresholding with morphological operations and U-Net model is proposed for accurate segmentation of mammogram images. The incorporation of attention mechanisms and residual connections in U-Net helps in enhancing the model's performance. The proposed model performs better than recent existing models, achieving high precision, recall, F1 score, accuracy, and area under curve (AUC). The proposed model is evaluated on the MIAS dataset and achieved an F1 score of 0.9764, precision of 0.9802, recall of 0.9980, accuracy of 0.9902, and an AUC of 0.99997. These results had shown significant improvements in comparison with existing models, making it a suitable and accurate model for the early detection and diagnosis of breast cancer.

Keywords: CAD; Otsu; Mammogram; MIAS; Segmentation; U-Net.

Mammogram image segmentation plays a vital role in early and timely detection of breast cancer. The segmentation helps in the detection of lesions from the image, which is the major region of interest for a radiologist. There are many existing methods for image segmentation, such as thresholding, region-based, edge-based, and cluster-based methods. However, these are now classified as traditional methods since learning-based methods are more widely used due to their higher accuracy. Learning-based methods for image segmentation include U-Net, Fully Convolutional Network (FCN), and Mask R-CNN, among others. Due to their robust nature, high accuracy, and precision, these learning-based methods have become the first choice for researchers. Nevertheless, learning-based methods still suffer from issues such as a false positive rate due to complexities like large datasets, long training times with augmentations, and a lack of domain knowledge. This section further presents an overview of the strengths and weaknesses of each traditional and learning-based segmentation model, highlighting their applicability and potential limitations in the context of mammogram image segmentation.

Traditional Segmentation Models

In this section, various image segmentation models along with their positive as well as negative points are discussed in table 1.

Image segmentation models discussed in table 1 are fundamental and still widely used for basic image analysis tasks. Among these methods most used models are discussed in detail below:

Otsu Thresholding Method: This is one of the most popular methods that separates the image foreground and background separately. In these methods an optimal threshold value is calculated every round using the maximum variance as parameter to separate foreground for background[1,2].

Adaptive Thresholding Method: This method works on the pixel intensity value in an image. A threshold value is computed based on the image size, contrast and variance. The pixels that had intensity above the threshold are separated as foreground and left become background pixels[3,4].

Region Based Method: This method works based on pixel and the color intensity in the image. The method splits an image into multiple small windows based on the homogeneous set of pixels. The region-based partitioning is done to separate foreground and background. The regions with similar pixel values are snipped under one window and this process traverses the complete image. This method helps in effective segmentation due to grouping of similar pixels[5].

Learning Based Segmentation Models

Various learning-based image segmentation models with their strengths and weakness are discussed in table 2. These models can capture complex patterns and details, making them suitable for advanced applications like medical imaging and autonomous driving.

Learning-based Image segmentation models discussed in table 2 can improve with more data makes them powerful tools in modern image analysis. Among these methods most used models are discussed in detail below:

U-Net Model: This is one of the most effective and the popular image segmentation models. The model architecture is in U shape as the reason model is named as U-Net where net is network. It uses the convolution layer for the feature extraction from the image and pool layer for the image compression. But due to the image compression the image is down sampled, and the up sampling is done using skip connection, which is computationally expensive[6,7].

Mask R-CNN: This is an extension of Fast R-CNN, that helps in predicting the segmentation mask. This model predicts the objects in the region, which are classified as ROI, as objects are the

Table 1. Summary of traditional image segmentation models

Traditional Image Segmentation Models		
Methods	Positive Points	Negative Points
Region-Based Segmentation[2]	• Effective for segmenting homogeneous regions. • Good for images with distinct regions.	• Can be computationally intensive. • Sensitive to the selection of initial seed points.
Thresholding[3]	• Simple and easy to implement • Fast processing time.	• Highly sensitive to noise and intensity variations. • Not suitable for complex images.
Watershed Segmentation[13]	• Good for separating overlapping objects. • Effective for images with well-defined gradients	• Can lead to over-segmentation. • Sensitive to noise and requires pre-processing steps.
Cluster-Based Segmentation[18]	• Can handle images with multiple regions. • Does not require prior knowledge of the image.	• May require a large number of iterations. • Sensitive to the initial choice of cluster centers.
Edge-Based Segmentation[22]	• Effective for detecting boundaries. • Works well for images with high contrast edges.	• Sensitive to noise. • May produce fragmented edges. • Not effective for images with smooth boundaries.

lesions that need to be segmented accurately. It uses the bounding boxes to mark the detected objects. This method is suitable for segmentation as well as object detection too from an image[8].

Fully Convolution Network (FCN): This model had a fully connected layer that is used for the replacement of convolution layers so that images of any size can be processed. Here each pixel in the image is assigned into a class. To up sample the image it has deconvolution layer, this up sampling is done using the created pixel class wise segmentation map[9,10].

Traditional methods for image segmentation are simple, fast, and effective for specific tasks but may struggle with complex patterns whereas learning based methods provide high accuracy and can learn complex patterns from data but require large, labeled datasets and significant computational resources. So, there is a need for an accurate and robust model that combines the strengths of both methods. In this work we are proposing a hybrid model for mammogram image segmentation using the traditional and learning segmentation method. This helps in creating a less expensive and domain specific accurate model. The proposed model uses the Otsu threshold with morphological operations for better foreground and background separation and U-Net learning model for accurate detection of ROI. The combination of traditional methods helps in retaining the domain knowledge like lesion boundaries marking which helps in overall enhancement of the model.

Literature Review

Authors proposed a deep learning-based hybrid model for the mammogram image segmentation[11]. The proposed method is based on U-Net and BCDU net. The authors combine both models to form a Bi- directional Convolution LSTM U-Net. The proposed network had shown the good Jaccard and dice coefficient score of 78.72% and 83.76% respectively. Also, the accuracy of Region of Interest (ROI) segmentation

Table 2. Summary of learning-based image segmentation methods

	Learning Based Segmentation Models	
Methods	Positive Points	Negative Points
U-Net[7]	• Focuses on relevant features. • Effective in complex medical imaging tasks.	• More complex architecture. • Increased computational and memory requirements.
Mask R-CNN[8]	• Combines detection and segmentation. • High accuracy for instance segmentation. • Handles occlusions well.	• Computationally expensive. • Requires extensive training time and resources.
Fully Convolutional Networks (FCN)[9]	• Improved gradient flow and feature reuse. • High performance on various segmentation tasks.	• May produce coarse segmentation boundaries. • Requires large, annotated datasets.
DeepLabV3+ [11]	• Handles multi-scale context. • Refines segmentation boundaries. • High performance on challenging datasets.	• Computationally intensive. • Requires significant computational resources for training and inference.
SegNet[13]	• Efficient memory usage. • Suitable for real-time applications.	• May struggle with fine details in segmentation. • Requires large amounts of labeled data for training.
DenseNet[23]	• Improved gradient flow and feature reuse. • High performance on various segmentation tasks.	• High memory usage. • May be prone to overfitting if not properly regularized.

is near 87%. The proposed model had reduced computational complexity by using LSTM with U-Net.

Authors used a Fuzzy C-Mean (FCM) method for mammogram image segmentation. The major goal of the paper is to enhance breast cancer diagnosis[12]. A hybrid method for segmentation is proposed using traditional methods like Contrast limited adaptive histogram equalization (CLAHE), morphological operations with FCM. The performance of the proposed method is evaluated on Mammographic Image Analysis Society (MIAS) dataset based on threshold, precision, sensitivity and specificity. The method had achieved the accuracy of more than 92% with 99% specificity.

Authors had discussed various existing segmentation methods based on traditional, machine and deep learning methodology[13]. The author had given emphasis on the fact that due to the cross disciplinary nature of this field, still there is no effective way to adopt the advancement in segmentation. The tumors are complex, and specialists could not understand the complex patterns and varying nature of tumors due to which developed models lack in varsity. The paper also concludes that the MIAS dataset is the most used dataset and U-Net is highest used model for the mammogram segmentation. The U-Net model does not need any annotated data as it is specifically developed for medical images segmentation only. Also, the models need high end GPUs for training making them complex for real time data processing.

Authors had proposed a connected U-Net model for the mammogram image segmentation. The author worked on encoder and decoder-based architecture[14]. The proposed model uses attention and residual Net for enhancement of the model which is evaluated using DDSM dataset with generated synthetic data using GAN. The proposed network architecture has two convolution units of 3 x 3 with ReLU activation and decoder block is of 2 x 2 size which is connected with previous output. The model has achieved the dice score of more than 95% with intersection over union (IoU) score around 92% on the used dataset.

Authors had used a hybrid method using Haar transformation and U-Net together for the breast tissue image segmentation for the MRI image[15]. The proposed model takes the lying position image of a patient that is equivalent to standing position for the preservation of the natural shape of the breast. The dataset images are labelled as skin, tissues and fats. The Haar transformation is used to reduce the information loss from the image and U-Net to learn the accurate features from labelling. The U-Net architecture is designed to prevent the problem of overfitting by adding the early stopping mechanism. The proposed model had shown the higher accuracy of around 90% with IoU of 87.48%. The proposed method is helpful for the plastic surgeons for the breast reconstruction surgery.

Authors had reviewed the deep learning-based methods widely used for the breast cancer image segmentation[16]. The author had concluded that the deep learning models are preferred over traditional models due to their accuracy and robustness.

Authors had proposed a dual branch-based U-Net for the breast ultrasound image segmentation[17]. The success of U-Net for the segmentation of the medical image segmentation motivated the author to develop a dual branch variant. The proposed model architecture uses two distinct paths for the model encoding helps in better feature extractions. At encoder path one the original image is inputted and at second path the image is created using robert edge filtering, which helps in highlighting and preserving the edges. The encoder paths then combine at convolution layer followed by a pool layer. The weighted scheme is used for cross learning. The proposed model is evaluated on the Breast Ultrasound Images (BUSI) and UDIAT dataset. The proposed method had achieved an IoU of 77.46% and the dice coefficient of 87.28%.

Authors had proposed a fused architecture for segmentation using Attendseg and gravitational clustering algorithm by using the mathematical data modelling[18]. The proposed work is done on breast ultrasound (BUS) images dataset. Initially the author did the preprocessing before the segmentation which helped in better segmentation and retaining the important features of the image. Further the proposed model of segmentation is used with the data augmentation. Attendseg is used to separate the ROI for the input images whereas the gravitational and mathematical modelling is issued for efficient feature extraction. The proposed method had achieved an accuracy of 98.95%, IoU of 85.63% and DC 89.45%.

Some more existing segmentation models are discussed below in table 3.

MATERIALS AND METHODS

To improve the existing segmentation techniques, a novel hybrid method for segmentation is proposed using Otsu thresholding with morphological operations and Deep Convolutional Neural Network (DNN) architecture inspired by U-Net. U-Net with Attention Mechanisms and Residual Connections are used to improve segmentation accuracy and robustness. This method only focuses on the segmentation phase, as preprocessing is already done using CLAHE and a VGG-inspired model.

Model Architecture

The key components of the architecture are:

Otsu thresholding: This method calculates an optimal threshold value to separate the background and foreground regions of the image. The Otsu threshold, T, is determined by maximizing the between-class variance, as shown in the equation 1 below:

Algorithm 1: Otsu Thresholding

Input Image I

1. $\forall$ I, $I_g = I(:,:,2) \therefore I_g = [P+1, \ldots\ldots. 255]$ s.t. P+1=Black and 255-Lightest
2. $\forall\ I_g.n_p \in \sum_{i=0}^{P+1} n_i \ \because n_i$ = group of pixels
3. Hist $(I_g)=n_i/N \ \because$ Hist$(I_g) \geq 0$, $\sum_{i=p}^{P+1} Hist\ (I_g) = 1$
4. Suppose $n_i = \{C_o, C_i\}$ s.t C_o = [P+1 ……. P*] and C_i= [p*+1 ……… 255]
5. $W_b = P\ (C_o) = \sum_{i=p+1}^{p*} Hist\ (I_g)$
6. $W_f = P\ (C_o) = \sum_{i=p*+1}^{255} Hist\ (I_g) = 1 - W_b$
7. The calculating mean of both C_o and C_i
8. $\mu_b = \sum_{i=p+1}^{p*} \frac{Hist\ (I_g)}{W_b}$, $\mu_f = \sum_{i=p*+1}^{255} \frac{Hist\ (I_g)}{W_f}$
9. Total mean $\mu_{TM} = W_b\ .\mu_b + W_f\ .\mu_f$
10. Class variance $\sigma_b^2 = \sum_{i=p+1}^{p*} \frac{(i-\mu_b)^2\ Hist(I_g)}{W_b}$
11. $\sigma_f^2 = \sum_{i=p*+1}^{255} \frac{(i-\mu_f)^2\ Hist(I_g)}{W_f}$
12. $Within\ Class\ variance\ \sigma_{wc}^2 = W_b.\sigma_b^2 + W_f\ .\sigma_f^2$
13. Between class variance $\sigma_B^2 = W_b.(\mu_b - \mu_{TM})^2 + W_f.(\mu_f - \mu_{TM})^2 = W_b W_f\ (\mu_b - \mu_f)^2$.
14. $\sigma_{TM}^2 = \sigma_{WC}^2 + \sigma_{BC}^2$
15. $p* = avg\ \{\max_{p+1 \leq i \leq 255}\{\sigma_{BC}^2(i)\}\} = avg\ \{\min_{p+1 \leq i \leq 255}\{\sigma_{WC}^2(i)\}\}$

$$\acute{o}^2{}_{B}(T)=\grave{u}_0\,(T)\grave{u}_1\,(T)[\grave{i}_0\,(T)”\grave{i}_1\,(T)]$$

In our method, we modified the Otsu thresholding by incorporating local adaptive techniques to accommodate the varying illumination conditions across the mammogram image. This improvement enhances the overall segmentation performance.

Morphological operations: Morphological operations are applied to the binary image obtained from the thresholding step. These operations, such as erosion, dilation, opening, and closing, can remove noise, fill gaps, and refine the segmented structures. We introduced a custom structuring element designed specifically for mammogram structures, which helps preserve the essential features and improve the segmentation quality.

U-Net: The U-Net architecture is a popular choice for segmentation tasks due to its encoder-decoder structure, which captures both high-level context and fine-grained details.

Attention Mechanisms: Attention gates are integrated to improve the focus on relevant features and reduce the influence of irrelevant regions. This helps in better delineation of the tumor boundaries.

Residual Connections: These connections help in mitigating the vanishing gradient problem, ensuring better gradient flow and making the network deeper and more robust.

The proposed model combines traditional and learning methods to take advantage of both methods.

The use of Otsu thresholding with morphological operations helps in making the model domain specific and to train model over smaller datasets. The Otsu thresholding with morphological operations is used for background and foreground separation, which helps in U-Net extracting accurate features from the images. The proposed U-Net follows the encoder decoder architecture based on convolutional layers as shown in figure 1, where encoder is used for the feature extraction and decoder is used to reconstruct the image to original resolution with minimum loss. The image is passed to the first two convolution layers of 3 x 3 kernel size and use 64 filters. A max pooling layer is present after every convolution layer that is nearly half the spatial dimensions of the image. This pattern follows up to Conv5 with the increasing filter from 128 to 1024. This helps the model in extracting the different features of the image. The high-level features from the image are captured using 16 x 16 x 1024. Further the decoder is used for the up sampling of the image, where created feature maps are enlarged to original input size of the image. After each up sampling a skip connection is used that helps in retaining the spatial information for better segmentation. These skip connections help in retaining the information that may be lost during encoding stage and results in poor segmentation. The model also uses an attention mechanism to better focus on the region of interest (ROI) and lesions. The residual connection helps in solving the issue of vanishing gradient, which helps training deeper networks. Also, In proposed model a total loss function is computed as combination of binary cross entropy and dice loss which helps in handling the issue of dataset classes imbalance.

Architecture Details

Encoder: The encoder part of the U-Net captures context through a series of convolutional layers followed by max-pooling. Each convolutional block in the encoder consists of:

- Convolutional Layer (3x3 kernel, padding, ReLU activation)
- Batch Normalization
- Convolutional Layer (3x3 kernel, padding, ReLU activation)
- Batch Normalization
- Max Pooling (2x2)

Attention Mechanisms: Attention gates are placed after each convolutional block in the encoder to refine the feature maps before passing them to the decoder. The attention mechanism calculates attention coefficients, which are used to weigh the importance of features.

Residual Blocks: Residual connections are added to each convolutional block to ensure better gradient flow and to improve the learning capability of the network. Each residual block consists of:

- Convolutional Layer (1x1 kernel, to match dimensions)
- Addition of input features and the convolutional output
- ReLU activation

Decoder: The decoder part of the U-Net upsamples the feature maps to the original input size, progressively combining them with the

Table 3. Existing Segmentation Models

Ref. No.	Datasets Used	Models Used	Primary Contribution	Advantages	Limitations
[19]	MIAS	FF-CSO Algorithm	Proposed a novel FF-CSO (Firefly-Competitive Swarm Optimization) algorithm for breast cancer detection in mammograms.	Improved detection accuracy by combining FF and CSO algorithms.	Limited evaluation on different datasets; requires further validation on larger datasets.
[20]	MIAS	Chan-Vese technique	Introduced the Chan-Vese segmentation technique for breast tumor segmentation in mammograms.	Provides a more accurate segmentation for homogenous regions within breast tumors.	Struggles with non-homogenous and noisy regions in mammograms.
[21]	MIAS	Level set with Cuckoo search optimization	Developed a hybrid segmentation approach using level set method enhanced with Cuckoo search optimization for mammogram segmentation.	High accuracy and robustness in identifying breast masses.	Computationally intensive; may not generalize well to other datasets or segmentation tasks.
[22]	MIAS	Non-Convex border optimization, segmentation thresholding	Proposed a non-convex border optimization approach for early detection of mammography edges and boundaries.	Early detection of edges and boundaries, improving the accuracy of tumor detection in earlier stages.	Limited focus on the segmentation of complex structures, which might affect overall performance.
[23]	MIAS, DDSM, CBIS-DDSM	Deep learning (InceptionV3, DenseNet121, ResNet50, VGG16, MobileNetV2), U-Net	Enhanced breast cancer detection with deep learning models, using CNN architectures and U-Net for segmentation.	High accuracy and robustness across multiple datasets; demonstrated superior performance across metrics.	High computational cost due to the complexity of the models used.
[24]	MIAS	Transfer learning with pre-trained	Introduced a novel transfer learning	High sensitivity and specificity, leveraging the	Requires extensive computational resources,

		CNN architectures	technique for automatic detection and classification of breast cancer.	strengths of pre-trained CNN models.	particularly for model training and tuning.
[25]	MIAS	Multi-objective Electromagnetism-Like Optimization Algorithm	Developed a multi-objective optimization algorithm for breast mass segmentation in mammograms.	Robust segmentation results with high accuracy and specificity.	Sensitivity could be higher; the model might be dataset-specific and less generalizable.
[26]	MIAS, DDSM, INbreast	Patchless Multi-Stage Transfer Learning	Introduced a patchless multi-stage transfer learning approach for improved classification of mammographic breast masses.	High accuracy and generalization across different datasets; eliminates the need for patch-based processing.	Patchless approach may not generalize well to all types of images, particularly those with irregular mass distributions.
[27]	MIAS, Custom Datasets	Fog Empowered Transfer Deep Learning	Proposed a fog computing empowered transfer learning model for enhanced breast cancer diagnosis.	High accuracy, sensitivity, and F1 score with efficient processing due to fog computing.	Requires specific fog computing infrastructure, which may not be universally available.
[28]	MIAS	Transfer Learning (AlexNet, Xception, ResNeXt, Channel Boosted CNN)	Proposed a transfer learning technique using various CNN architectures for breast cancer prognosis.	High accuracy, sensitivity, and specificity, with improved prognosis capability.	Focused primarily on classification; does not provide a detailed segmentation methodology.
[29]	MIAS	Atrous Pyramid Convolutional Deep Learning	Developed an Atrous Pyramid Convolutional deep learning approach for breast cancer detection and diagnosis.	Effective noise reduction and high detection accuracy, even in challenging cases.	Slightly lower sensitivity compared to other methods; may require fine-tuning for different datasets.
[30]	MIAS	Hybrid Model (EfficientNetB2, K-mean clustering, LSTM, CNN, Random Forest, Boosting)	Proposed a generic hybrid model for breast cancer classification using a combination of Efficient NetB2, K-mean clustering, LSTM, CNN, Random Forest, and Boosting.	High accuracy, sensitivity, and specificity; the hybrid model effectively leverages multiple techniques for improved classification.	Model complexity could pose challenges in implementation, requiring extensive computational resources and careful tuning.

Algorithm: Novel Attention-Enhanced Residual U-Net for Mammogram Image Segmentation

```
Input: Otsu + Morphological Image
Output: Segmented image S with pixel-wise classification (tumor, non-tumor)
1. Initialize the U-Net architecture parameters:
- Encoder layers: L_enc = {l_enc1, l_enc2, ..., l_encN}
- Decoder layers: L_dec = {l_dec1, l_dec2, ..., l_decN}
- Attention gates: A = {a1, a2, ..., aN}
- Residual connections: R = {r1, r2, ..., rN}
- Number of classes C = 2 (tumor, non-tumor)
- Learning rate á, Adam optimizer parameters, Dice loss weight ë_D, Cross-Entropy loss weight ë_CE
2. Define convolutional block ConvBlock:
Input: Feature map F_in
Output: Feature map F_out
ConvBlock(F_in):
F1 = Conv2D(F_in, filters=f, kernel_size=(3,3), padding='same')
F1 = ReLU(BatchNorm(F1))
F2 = Conv2D(F1, filters=f, kernel_size=(3,3), padding='same')
F_out = ReLU(BatchNorm(F2))
return F_out
3. Define attention gate AttnGate:
Input: Encoder feature map F_enc, Decoder feature map F_dec
Output: Refined feature map F_ref
AttnGate(F_enc, F_dec):
F_enc_att = Conv2D(F_enc, filters=f, kernel_size=(1,1), padding='same')
F_dec_att = Conv2D(F_dec, filters=f, kernel_size=(1,1), padding='same')
F_att = ReLU(F_enc_att + F_dec_att)
á_att = Sigmoid(Conv2D(F_att, filters=1, kernel_size=(1,1), padding='same'))
F_ref = á_att * F_dec
return F_ref
4. Define residual block ResBlock:
Input: Feature map F_in
Output: Feature map F_out
ResBlock(F_in):
F_res = Conv2D(F_in, filters=f, kernel_size=(1,1), padding='same')
F_out = ConvBlock(F_in) + F_res
return F_out
5. Encoder:
F_enc = I
for l in L_enc:
F_enc = ConvBlock(F_enc)
F_enc = MaxPool2D(F_enc, pool_size=(2,2))
F_enc = ResBlock(F_enc)
end for
6. Bottleneck:
F_bottle = ConvBlock(F_enc)
7. Decoder:
F_dec = F_bottle
for l in reverse(L_dec):
F_dec = UpSampling2D(F_dec, size=(2,2))
```

F_enc = corresponding F_enc from encoder
F_dec = Concatenate([F_dec, F_enc])
F_dec = AttnGate(F_enc, F_dec)
F_dec = ConvBlock(F_dec)
end for
8. Output layer:
S = Conv2D(F_dec, filters=C, kernel_size=(1,1), padding='same')
S = Softmax(S)
9. Loss function:
Define Dice Loss L_D:
L_D = 1 - (2 * Ó(y_true * y_pred) + å) / (Ó(y_true) + Ó(y_pred) + å)
Define Cross-Entropy Loss L_CE:
L_CE = -Ó(y_true * log(y_pred))
Total Loss L:
L = ë_D * L_D + ë_CE * L_CE
10. Training:
Initialize Adam optimizer with learning rate á
for each epoch:
for each batch (I_batch, y_batch):
F_enc = Encoder(I_batch)
F_bottle = Bottleneck(F_enc)
F_dec = Decoder(F_bottle, F_enc)
S_pred = OutputLayer(F_dec)
L_batch = Loss(y_batch, S_pred)
Backpropagate and update weights using Adam optimizer
end for
end for
11. Return segmented image S

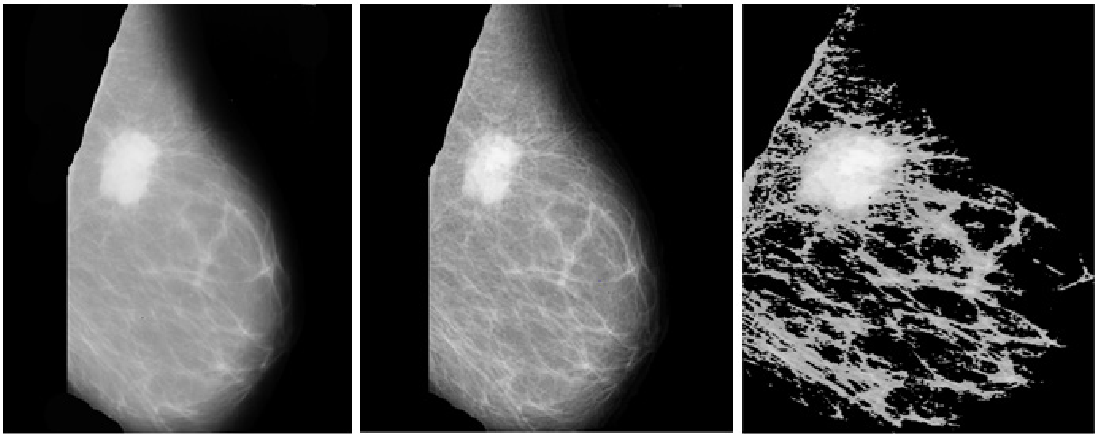

Fig. 1. a) Orignal Image; b) Enhanced Image; c) Segmented Image

corresponding encoder feature maps through skip connections. Each upsampling block in the decoder consists of:
• Transpose Convolutional Layer (2x2 kernel, stride 2)
• Concatenation with the corresponding encoder feature map
• Convolutional Layer (3x3 kernel, padding, ReLU activation)
• Batch Normalization
• Convolutional Layer (3x3 kernel, padding, ReLU activation)

• Batch Normalization

Output Layer: The final layer consists of a 1x1 convolution to map the features to the desired number of classes (e.g., tumor and non-tumor), followed by a softmax activation function for pixel-wise classification.

RESULTS AND DISCUSSION

The performance of the proposed hybrid model is evaluated on the MIAS dataset. The various performance parameters are calculated to evaluate the model like F1, recall, precision, accuracy and area under curve (AUC). The proposed model had achieved a high F1 score of 0.97 that is balancing the recall and precision, which shows that the proposed model is performing well. As the recall and precision of the proposed model is around 0.98, it indicates that the model has less or almost no false alarms. This shows that the proposed model can segment the lesions very accurately. Also, with the accuracy and AUC of segmentation over 0.99, the proposed model very accurately detects positive and negative cases. Below in Table 4 the existing models that use MIAS dataset are compared with our proposed model on

Table 4. Evaluation of Proposed Model

Ref. No	Model Used	Accuracy	Sensitivity	F1 Score	Precision	AUC
[23]	U-Net based segmentation	98.87%	98.98%	97.99%	98.79%	0.9888
[24]	Transfer learning with pre-trained CNN architectures	98.96%	97.83%	97.66%	97.35%	0.995
[25]	Multilevel multi-objective electromagnetism like optimization technique	98.93%	92.11%	—	—	—
[26]	Patchless approach eliminating need for patch separation	99.92%	99.87%	99.89%	—	1.00
[27]	Pre-trained deep learning models using Fog computing	99.1%	99.86%	99.37%	98.89%	—
[28]	Transfer learning-based segmentation approach	98.96%	98.5%	98.5%	98.78%	0.997
[29]	Quantum Wavelet Transform (QWT) filtering, Atrous pyramid CNN	98.57%	92%	—	98.57%	0.8877
[30]	Efficient NetB2 +MGSVM	99.47%	99.31%	99.44%	99.44%	0.9944
Proposed hybrid Model	Otsu thresholding + Attention ResUNet	99.02%	99.80%	97.64%	98.02%	0.99997

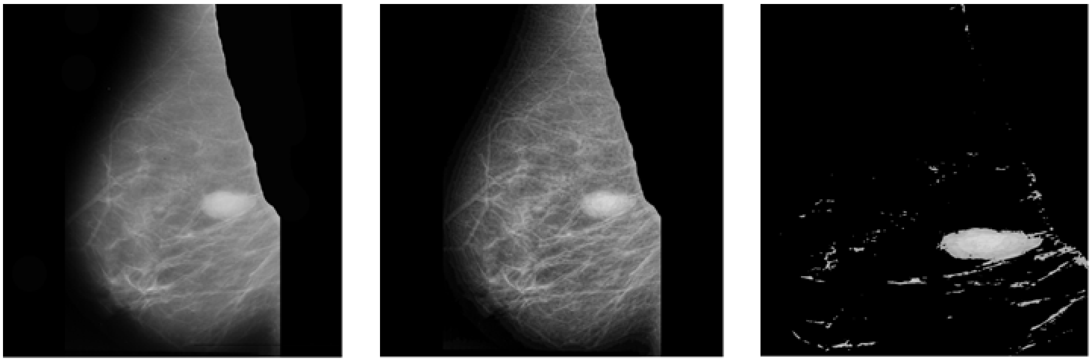

Fig. 2. a) Orignal Image; b) Enhanced Image; c) Segmented Image

the basis of various evaluation metrics like F1, precision, recall, accuracy, AUC.

As shown in Table 4, the proposed model outperforms in contrast with existing models. The proposed model initially uses the Otsu thresholding method which helps in accurately classification of background and foreground pixels, which helps in calculating the optimal threshold. Further morphological operations are applied that help in refining the binary image. Then the image is fed to U-Net architecture where encoder and decoder architecture helps in extracting fine details and features. The integration of attention mechanism helps the model only to focus on ROI instead of other irrelevant areas which ensure accurate marking of tumor boundaries. The model is robust as it also uses residual connection to solve gradient problem.

Figure 1 and 2 above shows the original image in pgm format as in MIAS dataset. There is a total of 322 such images in MIAS dataset. The next image is an enhanced image which is denoised using the CLAHE and VGG inspired network. CLAHE is used for contrast correction and VGG inspired is proposed learning model that is trained over noisy images to understand the complex pattern of noise and various artifacts in images. The noise is generated in images using noise synthesis, and the images are used to train models to understand noisy image patterns and to denoise the image. The model is evaluated based on PSNR value. Further the segmented image is shown. The segmented image clearly shows the lesions or ROI part removing all the irrelevant area. This helps the radiologist and a learning model to classify the segmented images correctly as benign or malignant. The proposed methodology is quite accurate and useful for future classification.

CONCLUSION

In this paper a hybrid model for segmentation using mammogram images is proposed based on Otsu thresholding with morphological operations and U-Net. The integration of traditional and learning methods lays a strong foundation to develop an efficient segmentation architecture. The goal of the segmentation model is to decrease the false detection rate for the accurate diagnosis. The adaptive filtering in Otsu thresholding helps in better classification of similar pixels and create accurate homogeneous pixel sets for foreground and background and morphological operations helps in prevention of the edge's structures. The preservation of edges is very important for further U-Net to identify the tumor boundaries pattern. U-Net will learn the boundaries patterns and help in accurately segmenting the tumor. The incorporation of attention mechanism, residual and skip connection also helps in enhancing the model performance. The model had attained accuracy, AUC and precision around 99%, which makes the proposed model accurate. In future, the segmented data will be further used for the classification task.

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Ethics Statement

This research did not involve human participants, animal subjects, or any material that requires ethical approval.

Informed Consent Statement

This study did not involve human participants, and therefore, informed consent was not required.

Clinical Trial Registration

This research does not involve any clinical trials

Author's Contribution

V.S. (Vandana Saini): Design of segmentation model, Implementation and manuscript writing, Manuscript communication; M.K. (Meenu Khurana): Suggestion regarding design of segmentation model, Visualization, Supervision, manuscript writing – review & editing, approval of manuscript; R.K.C (Rama Krishna Challa): Suggestion regarding design of segmentation model, visualization, approval of manuscript and Supervision.

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