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EU-NET: Deep Reinforcement Learning Aided Breast Tumor Segmentation and Attention based Severity Classification using Fused Ultrasound and Mammography Images

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breast tumor detection, mammograms images, ultrasound images, tumor segmentation, severity grading

Abstract

Breast cancer is increased gradually during the past few years, which is the second leading disease diagnosed in women. Hence, early detection of breast cancer is one the way to reduce mortality. Ultrasound and mammography are an excellent diagnosing technique for breast tumors, but their identification and classification have many challenges. Hence, it limits with less accuracy, true positive rate, and high false positive rate. To overcome these issues, we proposed EU-Net model which includes three major processes such as three stage preprocessing, dual agent-based segmentation, and breast tumor severity classification. Initially, noise removal is performed by hybrid filters (wiener and fuzzy filters) which provides noiseless image. After that, contrast enhancement is performed by Advanced Contrast Limited Adaptive Histogram Equalization (A-CLAHE) which enhances the image contrast by adaptively change the clip limit and histogram. The preprocessed ultrasound and mammography images are fused by Undecimated Discrete Wavelet Transform (UDWT) and Independent Component Analysis (ICA) which utilizes both the information of ultrasound and mammography which also increases segmentation and classification accuracy. In second, Dual Agent-Deep Q Network (DA-DQN) algorithm is proposed for segmenting the tumor region by considering various features. Finally, Enhanced U-Net (EU-Net) is proposed for severity classification based on segmented region which classifies the images into three classes such as normal, moderate, and severe. The simulation of this research is conducted by Matlab simulation tool and the performance of this research is evaluated by various performance metrics by considering two public datasets namely Breast UltraSound image (BUS) dataset and Digital Database for Screening Mammography (DDSM) dataset.

1. INTRODUCTION

In recent days, death of women is mostly due to breast cancer mortality which is common cancer that increases the fatality rate. Early diagnosis and treatment of breast cancer reduce the mortality rate [1]. In previous years, manual diagnosis of breast cancer is performed by the doctor using mammograms and ultrasound images. However, manual diagnosis does not provide accurate results which leads to various inconveniences related to evaluating the presence of cancer when the woman

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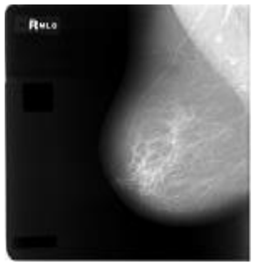
does not have any cancer and vice versa [2]. The rapid development of health and medical services establishes automatic detection of breast cancer using various equipment. Various types of images such as MRI, CT, mammogram, ultrasound is used to detect breast cancers [3], [4].

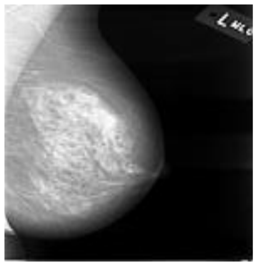
In general, medical images have certain noise which is removed by performing preprocessing using various methods. In preprocessing phase, the extraction of ROI is performed by subtracting the unwanted background areas using normalization method. Cancer cell detection in the breast portion is performed by various processes such as asymmetric analysis, color analysis, etc. But, the detection of breast cancer must have the information of edge region and geometrical orientation. Image fusion is performed in several state-of-the-art works in terms of adding noise to the image to maintain the real-time scenario. However, that reduces the segmentation and classification accuracy. Segmentation of breast image is mainly performed to detect breast cancer [5]. The segmentation results will provide impact on classification results either positive or negative. Various types of segmentation were performed in several works such as manual, automatic, and semi-automatic segmentation. Various deep learning approaches are used to perform segmentation as well as classification. However, the segmentation results are affected by presence of pectoral muscles and microcalcification in the image which reduces the segmentation accuracy by segmenting the microcalcification area as tumor region [6]-[9].

Feature extraction is performed to classify the breast tumors in which the cancer area feature is extracted by considering several features such as textural features, edge features, etc. The spatial and structural features are mainly extracted to classify the breast tumors. Several datasets are used to detect the breast tumor in the deep learning model such as BUS, INbreast, MIAS, DDSM, etc. Various machine learning and deep learning algorithms such as SVM, KNN, RF, CNN, VGG-16, YOLO, etc., are used in several works to classify the breast tumor into several classes such as normal, malignant, and benign [10]-[15]. However, the classification accuracy is somewhat reduced due to redundant features. To overcome these issues, we proposed this research which provides efficient solutions to all these problems.


(a)


(b)


(c)


(d)

A. Aim & Objectives

The main aim of the research is to effectively segment the breast tumors for classification based on their severity level using fusing of images such as ultrasound and mammography. In addition, the various existing research problems are also addressed in this work based on segmentation and classification accuracy. The major objective of this work is to enhance the segmentation and classification accuracy during the diagnosis of breast cancer using fused images. Some of the sub-objectives are as follows,

- To alleviate the noise and enhance the image quality of the input image by performing three-stage pre-processing which also enhances the results during segmentation and classification respectively. The useful information of the images is ensured by performing images fusion.
- To reduce the run time complexity and achieve better segmentation results, deep reinforcement learning-based

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Journal of Coastal Life Medicine

segmentation is performed which enhances the segmentation accuracy.

- To achieve less false-positive rates and enhanced classification accuracy by performing attention-based feature extraction and classification which reduces the feature redundancy and provides better classification results.

B. Research Motivations

The segmentation and detection of breast tumors have faced numerous problems in recent studies based on preprocessing, extracting features, and classification of breast tumors. Several state-of-the-art works provide various solutions to overcome these issues. However, it provides poor results due to lack of efficient approaches. Several major problems are addressed from the previous works which are sorted as follows,

- **High False Positive Rate:** Preprocessing of the input breast images enhances the quality of the images. Several previous methods perform preprocessing in terms of noise removal and contrast enhancement. However, lack of considering the boundary of the images increases the false positive rate.

- **Poor Segmentation:** Segmentation was performed in some existing works to segment the breast lesions and tumors. However, lack of removing the micro-calcification and pectoral muscle.

- **Inaccurate Classification:** Feature extraction was performed to classify the breast tumors in several works by considering textural and edge features only. However, these features are not enough to perform accurate classification of breast tumors. In addition, high feature redundancy also reduces the classification performance.

C. Research Contributions

In this paper, we proposed EU-Net model for breast tumor severity grading using fusion of mammograms and ultrasound images. The contributions of this research are defined as follows,

- In first, we perform three stage-based pre-processing to reduce noise and blurriness of the images. For noise removal, we used hybrid filters which preserves the edge information and provide noise free images for segmentation. Here, contrast enhancement is performed by A-CLAHE algorithm for increasing the brightness of the image. Data augmentation is performed to increase the training accuracy.

- In second, image fusion is performed by UDWT-ICA algorithm which fuses both ultrasound and mammograms images for utilizing the information of both images which increases segmentation and classification accuracy.

- In third, segmentation is performed by DA-DQN algorithm which includes two agents for segmentation. The first agent performs background suppression and second agent perform region extraction by considering several features (tumor density, blood flow, location, size, and diameter) which increases segmentation accuracy and true positive rate.

- Finally, breast tumor severity classification is done by EU-Net which classified the tumors into three classes such as normal, moderate, and severe by considering many features which reduces the false positive rate and increases true positive rate.

The performance of this research is estimated based on accuracy, precision, recall, f-measure, computation time, and ROC curve.

D. Paper Organization

This remaining section of this research is organized as follows; Section II illustrates the literature survey which includes the research gaps of the existing works. Section III explained the major problems are addressed in this research. Section IV

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Journal of Coastal Life Medicine

illustrates the research methodology of the proposed EU-Net model which includes processes, pseudocode and mathematical representations. Section V explains the experimental results which includes comparison and simulation environment of this research. Section VI concludes the proposed EU-Net model with future directions in a detailed manner.

2. LITERATURE SURVEY

In paper [16], authors proposed segmentation and recognition of breast cancer using digital mammography images. The proposed work includes two phases such as image segmentation and recognition. Here, RGB images were considered with WSI format which was collected and stored in the database. After that, noises were removed by using filtering method, and smoothening is performed by interpolation method. The preprocesses images were trained in the document management phase. From the preprocessed image the three types of features were extracted for breast cancer identification which was textural, morphological, and spatial features. The simulation results demonstrate the proposed work achieved better performance in terms of interpretability and accuracy. However, limited features were considered for breast cancer segmentation and recognition which was not enough for accurate breast cancer that leads to poor classification accuracy and high false-positive rate.

Authors in [17] proposed a novel for breast cancer detection using hybrid machine learning algorithm. Initially, preprocessing was performed by using median filtering algorithm for obtaining noise-free images. Then perform background elimination for detecting the objects from the images. Here, hybrid machine learning algorithm was used for masking the affected region to increase accuracy. From the affected region, features are extracted for identifying breast cancer. The performance of the proposed work is evaluated based on MIAS dataset. Here, machine learning algorithm was proposed for breast cancer detection. However, it takes much time for training for larger dataset which leads to high latency during cancer detection.

A novel deep learning algorithm was proposed fordiagnosing breast cancer using MRI images [18]. Initially, the noises are removed from the input images using wienmed filter which includes both wiener filter and median filter. The preprocessed images are fed into backpropagation boosting recurrent wienmed with hybrid optimization algorithm to classify the breast cancer severity. Here, feature extraction was performed based on grey level co-occurrence matrix algorithm. Finally, the proposed hybrid algorithms classified the image as benign or malignant. The performance of this work was evaluated based on breast MRI dataset.

Authors in [19], proposed a breast cancer segmentation method using improved salp swarm optimization algorithm. Here, quick shift algorithm was proposed for extracting the pixels from the images. based on extracted pixels segmentation was performed based on the proposed optimization algorithm. From the segmented results, this research identified breast cancer. The experimental results demonstrate the proposed work achieved better performance compared to traditional salp swarm optimization. Here, quick shift method was proposed for extracting the pixel information from the image which leads to high accuracy however, optimization algorithm does not suitable for larger datasets due to its slow convergence

Inpaper [20], authors proposed an approach to perform detection of breast cancer by ultrasound images. Four processes were performed in this work such as preprocessing, breast cancer segmentation, extraction of features, and classification. Initially, noise removal was performed in the preprocessing stage using SRAD diffusion. Segmentation was performed by extracting the ROI using AC-based segmentation. Feature extraction was performed by extracting the textural features. Finally, classification of cancer by the textural features into three classes such as benign, normal, and malignant. Three classifiers were used to extract the features and performed classification such as KNN, decision tree, and random forest algorithm.Here, preprocessing was performed by removing the speckle noise. However, lack of considering the intensity of the

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Journal of Coastal Life Medicine

images reduces the accuracy of classification results.

Inpaper [21], authors proposed an approach to perform segmentation of breast tumors based on mass of tumors using cascaded U-Nets. Two U-Nets are connected using improved skip connections for performing efficient breast image segmentation. Contextual information was emphasized by integrating the connected U-Nets with ASPP pooling using encoder to decoder network. This model was implemented using two network architectures such as residual U-Net and attention U-Net. CBIS-DDSM, INbreast, and a private dataset were used to evaluate the proposed method. Cycle-GAN model was used to perform experiments by enhancing and augmenting the images from the two various datasets. However, breast tumor segmentation was performed by using connected U-Net using mammogram images. However, the segmentation accuracy was reduced due to presence of noise in the images.

In this research, authors proposed an approach to perform detection of breast cancer using histopathological images using deep learning approach [22]. Four major phases are performed in this method such as preprocessing, segmentation, feature extraction, and classification of breast tumors. Initially, preprocessing and segmentation was performed by Multi-controlled Watershed Segmentation Algorithm (MWSM) in which Sobel filter was used to remove various image factors. CNN and LSTM were combined as CLSTM which consists of SDC and LSTM model to train the processed HP images to extract the features using SVM classifier for performing classification of breast cancer. BreakHis dataset was used to evaluate this work. The segmentation of breast cancer was performed using MWSA algorithm. However, lack of removing the background of the images degrades the segmentation results.

In paper [23], authors proposed an approach to perform classification of breast tumors using ultrasound images by fusing the extracted features. Initially, image decomposition was performed for the mask and actual ultrasound breast images by implementing bilateral filtering, fuzzy enhancement, and morphology operation. Bilateral filtering was performed to remove the noises and fuzzy enhancement was used to enhance the ultrasound images and morphology operation was performed to overcome the edge complexity and blurriness. Feature extraction was performed from the decomposed image and fusing the features using RGB fusion method by implementing transfer learning. Finally, ANN was used to classify breast tumors into malignant and benign.Here, classification of breast tumor was performed by extracting the features from the fused images. However, lack of considering the pectoral muscle and microcalcification during classification reduces the classification accuracy.

Machine learning algorithm based micro calcification detection was performed in this research [24]. The first process of this research is normalization which help to modify the intensity ranges of the pixels. After that image registration was performed by affine transformation. To remove the low intensity pixels, the images were converted into binary format. Finally, feature extraction (i.e intensity feature, shape feature, and statistic feature) and classification was done by six machine learning algorithms namely SVM, KNN, decision tree, naïve bayes, LDA, and decision tree. However, machine learning takes much time for training which increase training latency and reduce training accuracy due to support smaller dataset.

Deep learning-based breast cancer detection is performed in this paper [25]. Initially, noise removal was done by utilizing median filter, after that CLAHE algorithm was proposed to enhance the contrast of the image. Finally, CNN algorithm was used to extract the features from the image for classifying the image into normal or abnormal. Here, median filter is used to remove the noise from the images, however it does not focus onremoving blurriness of the images which reduces the quality of the image that leads to poor detection accuracy.

An automated CAN model is proposed for detecting breast cancer using deep learning approaches [26]. Initially, image resizing was performed automatically to reduce the complexity. Then, augmentation was performed to increase the performance of detection by improving the dataset

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Journal of Coastal Life Medicine

size. Here, pixel wise segmentation was performed to extract the ROI of breast. Finally, CNN algorithm performed classification based on the segmented region, which classified the images into two major classes such as normal and malignant.

Intellectual mechanism was proposed for breast cancer detection using mammogram images [27]. Preprocessing was done by median filter which reduces the noise from the images. After completed preprocessing, feature extraction was performed by K-means clustering algorithm. Finally, SVM algorithm performed classification which includes three classes namely benign, normal, and malignant. The comparison results show that the proposed work achieved better performance in terms of sensitivity, accuracy, ROC, and specificity. However, this research provides less accurate results due to the presence of illumination, and blurriness.

3. Problem Statement

In paper [28], authors proposed an approach to perform breast lesions segmentation using U-Net by multiple fusion of features for large-scale breast lesions by consisting of two modules with a loss function. The major problems of this research are listed as follows,

- In this work authors mainly focused on efficient segmentation of breast lesions in large-scale variations using BUS dataset. However, presence of noise in the images degrades the quality of the breast images which leads to poor segmentation of breast lesions.
- Here, segmentation was performed by considering texture and edge features of the breast lesions. However, these features are not adequate to perform efficient segmentation which increases the false positive rate.

In paper [29], authors proposed an approach to perform segmentation of breast tumors by week-supervised deep learning approach using ultrasound breast images. Here, anatomy decomposition was performed to decompose the breast image. Then segmentation was performed by class activation mapping and deep level set (CAM-DLS) method. The main problems of this research are explained as follows,

- Here, segmentation was performed by considering the mammary gland and fat from the anatomical structure. However, the presence of microcalcification in the images increases the false positive rate.
- In this work, segmentation was performed with including background of the ultrasound image that leads to consider unwanted features for performing segmentation which increases the segmentation complexity.
- Class activation mapping was performed to perform breast tumor segmentation but, lack of considering the boundaries (i.e., edge) information of the image leads to poor segmentation results.

Authors in [30] proposed an approach to perform detection of breast cancer using mammography images by fusing the features of the breast mammogram images. The major drawbacks of this research are listed as below,

- In this paper, noise removal was performed using Bayes-Shrink soft thresholding technique. However, poor noise removal was performed when the wavelet coefficients is greater than the threshold which increases the false positive rate.
- Segmentation was performed by considering the threshold technique to extract the ROI with background. However, lack of considering the pectoral muscle and microcalcification leads to poor segmentation accuracy.
- Five ANN classifiers were used to classify the breast tumor based on fused features by considering only textural features. However, implementation of five classifiers increases the examination time which leads to inaccurate classification due to insufficient features.

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Journal of Coastal Life Medicine

In paper [31], authors proposed a method to perform detection and classification of breast tumors using mammogram images by implementing improved YOLOv5 neural network. The major issues of this research are defined as follows,

- Here, authors performed preprocessing of the breast images to improve the quality of the images. However, preprocessing was performed without considering the edge information that reduces the tumor detection accuracy.
- Classification of breast tumors was performed into two classes by annotating the dataset. However, lack of considering the microcalcification information increases the false positive rate.
- In this work, improved YOLOv5 algorithm was used to perform classification by selecting efficient model. However, this algorithm is not suitable to detect small-shaped tumors which leads to inaccurate classification results.

Research Solutions:

In preprocessing, noise removal is performed by implementing hybrid filters (i.e., wiener filter-fuzzy filter) which remove the noise and invert the blurriness with edge preservation that improves the accuracy of segmentation. In addition, image fusion is performed after preprocessing of both ultrasound and mammogram images which also improves the segmentation results. Data augmentation is performed in this work which considers the geometrical orientation of the breast images for performing rotation or flipping to increase the true positive rate. Segmentation is performed by implementing DA-DQN algorithm considering numerous features such as tumor density, blood flow, etc., which reduces the false positive rate. The microcalcification and pectoral muscles are considered and removed in the segmentation process which reduces the false positive rate. Enhanced U-Net is used to perform feature extraction and classification of breast tumors by considering only the un redundant features and multiple features are considered for performing classification such as sphericity, degree of circularity, average intensity, etc., which increases the classification performance.

4. Proposed Work

This research mainly focused on enhancing the segmentation and classification accuracy of low contrast input breast images during breast tumor segmentation by fusion approach. The mammography and ultrasound images are fused in this work in which the fused images hold the significant information than the single images. The proposed work acquires images from the Breast UltraSound image (BUS) dataset and Digital Database for Screening Mammography (DDSM) dataset for breast tumor segmentation. Fig 1 represents the proposed work architecture which includes the process following,

- Three Stage Pre-processing
- Dual Agent-based Segmentation
- Breast Tumor Severity Classification

A. Three Stage Pre-Processing

At initial stage, the breast images are acquired from the BUS and DDSM datasets are fed for pre-processing. The pre-processing of input images removes the noise and improves the image quality that providing better results during segmentation and classification respectively. The pre-processing of both the mammography and ultrasound images are done separately in a simultaneous manner. The steps involved in pre-processing are,

a. Hybrid Noise Removal

The acquired images generally contain noises that reduce the quality of images and affect the performance of the method. The proposed work aims to remove the noise in the images by *Hybrid Filters (i.e., Wiener-Fuzzy Filters)*. The combination of these filters improves the noise removal capability in terms of image smoothing, edge preservation, and inverting the blurriness effect. The ultrasound and mammogram images include four types of noises such as salt and pepper noise, gaussian noise, speckle noise, and impulse noise.Initially, the noisy images are fed into wiener filter for reducing Gaussian noise, speckle noise,

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CODEN: JCLMC4
Journal of Coastal Life Medicine

and blurriness of images simultaneously. The mathematical representation of the wiener filter is defined as follows,

$$WF = \frac{C^*}{|C|^2 + N} \quad (1)$$

$$N = \frac{1}{SNR} \quad (2)$$

Where C represents the function of degradation C^* represent the complex conjugate of C, and N represents the reciprocal of SNR. In this way, noise (speckle, Gaussian) and blur are removed from the images. Then the images are fed into fuzzy filters to remove the remaining noises such as salt and pepper noise, and impulse noise which also preserves the edge information of the images. The membership function of the fuzzy filters is implemented as a trapezoidal model which is defined as follows,

$$f_z(I; p, q, r, s) = \begin{cases} 0\,, if I \le u \\ \frac{I-p}{v-p}, if p \le I \le q \\ 1, if q \le I \le r \\ \frac{s-I}{s-r}, if r \le I \le sI \\ 0, if\ s \le I \end{cases} \quad (3)$$

Where I represent the vector of input, and p, q, r, s represent the scalar parameters which are used for locating the shoulder and feet of the trapezoidal model. The values of these scalar parameters are listed as below,

$$p = a1 \times \text{Min}\,\{\mu_i, \mu_j\} \quad (4)$$

$$q = a2 \times \text{Max}\,\{\mu_i, \mu_j\} \quad (5)$$

$$r = a3 \times q \quad (6)$$

$$s = a4 \times r \quad (7)$$

Where $a1, a2, a3, a4$ represent the adjustable parameters, andμ_i and μ_j represents the neighborhood mean in pixel i and image mean containing noise. The weight values of the fuzzy filters are adaptively based on their noise values.

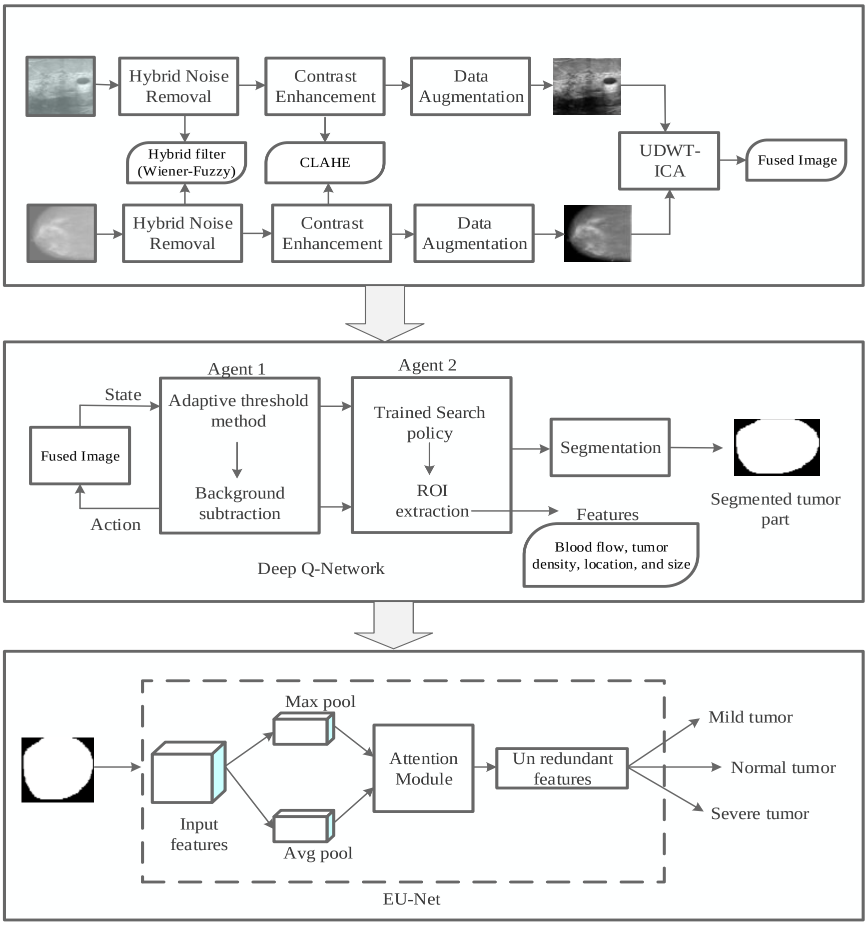

Fig.1 Architecture of proposed EU-Net model

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Journal of Coastal Life Medicine

b. Contrast Enhancement

The noise-removed images are fed for contrast enhancement which improves the quality of image. The proposed work acquires high contrast images by Adaptive *Contrast Limited Adaptive Histogram Equalization (ACLAHE)* method which works over an images' tile instead of working on entire image. The utilization of ACLAHE enhances the image brightness by adaptively equalizing the histogram.The proposed ACLAHE overcomes the traditional drawback of the CLAHE algorithm which dynamically changed the clip limit based on the edge information. The process of ACLAHE is explained as follows,

Initially, the noised removed images are partitioned into equal sizes without overlapping. The regions are clustered into three groups such as inside region(I_R), corner region(C_R),, and boundary region(B_R), based upon the position. After dividing the region, histogram calculation is performed for every region and also perform histogram clipping with respect to the limit of clip. Additionally, the clip limits are dynamically changed to calculate the function of cumulative distribution. Finally, bilinear interpolation is performed to map the grid points in the pixel with respect to estimated function of cumulative distribution. The clip limit of ACLAHE is calculated as follows,

$$\delta = \frac{P_n}{g}\left(1 + \frac{\alpha}{100}(Max_s - 1)\right) \qquad (8)$$

where δ represent the limit of clip and P_n is a number of pixels and$g$ represent the gray scale, α denotes the clipping coefficient.The transformed value of the pixels$(T_{p_{new}})$is defined as follows,

$$T_{p_{new}} = \frac{o}{h+o}\left(\frac{k}{l+k}M_{i-1,j-1}\left(T_{p_{old}}\right) + \frac{l}{l+k}M_{i,j-1}\left(T_{p_{old}}\right)\right) + \frac{h}{h+o}\left(\frac{k}{l+k}M_{i-1,j}\left(T_{p_{old}}\right) + \frac{l}{l+k}M_{i,j}\left(T_{p_{old}}\right)\right) \qquad (9)$$

where $M_{i,j}$ represent the mapping function of the pixels in the region (i,j) which equally distributes the histograms in the images which leads to high image quality. The process of contrast enhancement increased the quality of the breast images which provides accurate detection results. Fig 2 represents the bilinear interpolation algorithm for proposed A-CLAHE algorithm.

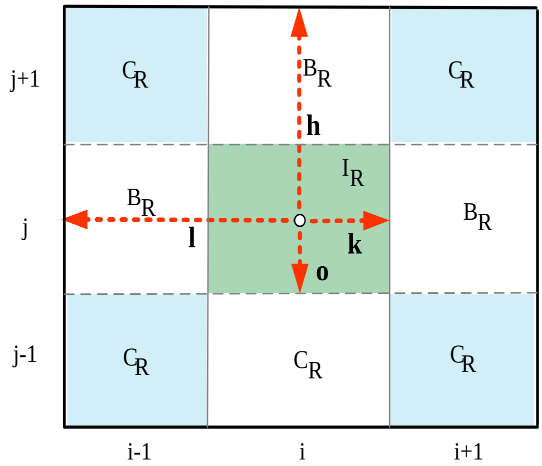

Fig.2 A-CLAHE based bilinear Interpolation

c. Data Augmentation

The contrast-enhanced images are augmented to improve the training images dataset. The proposed work performs data augmentation by rotation and flipping.In which the flipping provides a mirror image of a breast image for both vertical and horizontal axes. Mostly horizontal flipping is favored compared to vertical flipping, because the bottom and top information of the image does not change always. For BUS, and DDSM dataset most the images are present on the left side, hence we need to make a uniform direction of breast images to increase the detection accuracy. The rotation of the images is also performed in this research. Here, breast images are rotated both rightside and left side into some degrees such as$90^\circ, 180^\circ, and\ 270^\circ$. The rotation process is probably safe on breast image datasets. This type of transformation results is called as data augmentation. Fig 3 represents the sample data augmentation of contrast enhanced mammograms images.

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Journal of Coastal Life Medicine

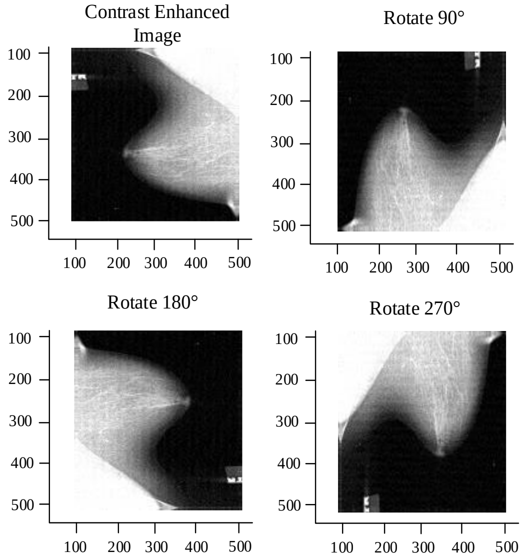

Fig.3 Sample images for Data augmentation

After completing the three-stage pre-processing, both the pre-processed images are fused to achieve high segmentation accuracy as the fused images contain more specific information. The image fusion is done by utilizing the combination of Undecimated Discrete Wavelet Transform (UDWT)and Independent Component Analysis (ICA) which is shown in fig 4.Here, two types of images (i.e ultrasound and mammography) are fed into UDWT for acquiring HFSs and LFSs. Then, the LFSs coefficients are combined to get fused image of LFS by utilizing the maximum selection rule. The mathematical representation of fused coefficients is listed as follows,

$$F_{LFS} = \begin{cases} LFS_j^{\bar{I}1} & if LFS_j^{\bar{I}1} \geq LFS_j^{\bar{I}2} \\ LFS_j^{\bar{I}2} & otherwise \end{cases} \qquad (10)$$

where F_{LSF} represent the fused image of LFS, and $LFS_j^{\bar{I}1}$, $LFS_j^{\bar{I}2}$ represent the subbands of low frequency LFS image and j represent the region of image for $\bar{I}1(a,b)$ and $\bar{I}2(a,b)$. The HFSs coefficients are segmented into numerous regions. The changed spatial frequency of two source images of HFS are defined as follows,

$$MSF = \sqrt{(rf)^2 + (cf)^2 + (df)^2} \qquad (11)$$

where rf, cf, df represent the column frequency, row frequency, and diagonal frequency respectively.

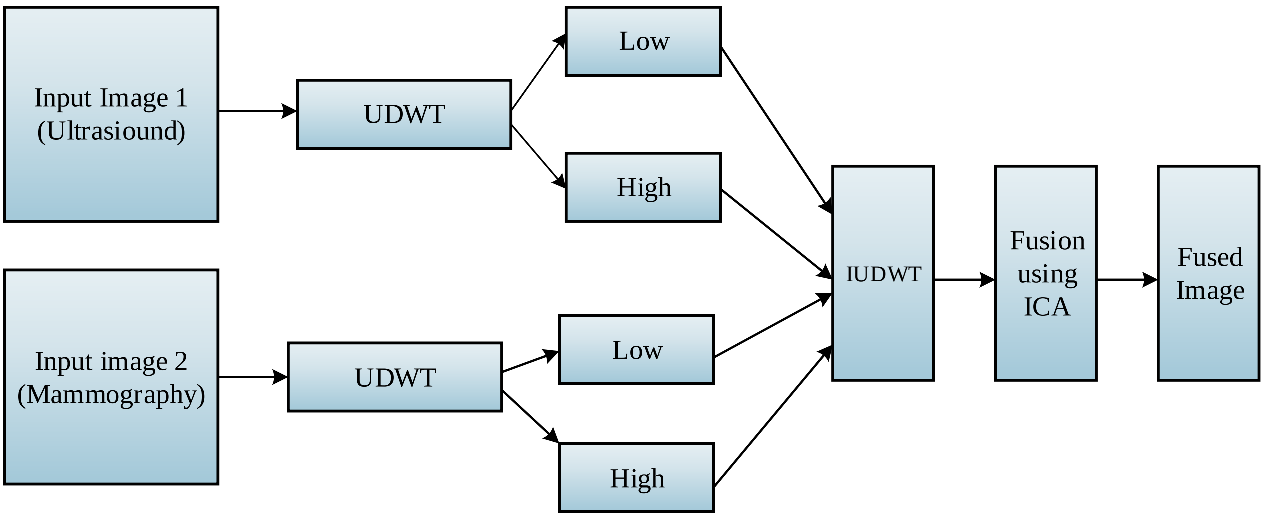

Fig.4 Flowchart of Image Fusion using UDWT-ICA methods

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CODEN: JCLMC4
Journal of Coastal Life Medicine

$$rf = \sqrt{\frac{1}{mn}\sum_{a=1}^{m}\sum_{b=2}^{n}[f(a,b)-f(a,b-1)]^2} \quad (12)$$

$$cf = \sqrt{\frac{1}{mn}\sum_{a=2}^{m}\sum_{b=1}^{n}[f(a,b)-f(a-1,b)]^2} \quad (13$$

$$df = z + s$$

$$z = \sqrt{\frac{1}{mn}\sum_{a=2}^{m}\sum_{b=2}^{n}[f(a,b)-f(a-1,b-1)]^2} \quad (14)$$

$$s = \sqrt{\frac{1}{mn}\sum_{a=2}^{m}\sum_{b=2}^{n}[f(a-1,b)-f(a,b-1)]^2} \quad (15)$$

Where MSF reflect the changes in texture, detailed difference, and image entire activity level. If the MSF is higher then the image also has high determination. The calculation of fused HFS is defined as follows,

$$F_{HFS} = \begin{cases} HFS_j^{\bar{I}1} & if MSF_j^{\bar{I}1} \geq MSF_j^{\bar{I}2} \\ HFS_j^{\bar{I}2} & otherwise \end{cases} \quad (16)$$

where F_{HFS} represent the fusion of HFS, and $MSF_j^{\bar{I}1}$represent the changed spatial frequency of image $\bar{I}1(a,b)$and $MSF_j^{\bar{I}2}$ represent the modified spatial frequency of image $\bar{I}2(a,b)$. After that, inverse UDWT is performed to obtain the fused image of HFS and LFS images which is computed as follows,

$$FI = I\text{UDWT}\ (F_{HFS}, F_{LFS}) \quad (17)$$

Where FI represent the fused image of LFS and HFS, after that apply ICA algorithm to FI for getting final fused image. The inverse operation is applied to ICA to get reconstructed image$\text{FI}^{(ICA)}$. The combined fused image is defined as below,

$$FI = \sum \text{FI}^{(ICA)} \quad (18)$$

The use of UDWT-ICA method performs downsampling to reduce the spatial resolution of image thereby acquiring high precision fused image.

Pseudocode for Preprocessing
1. Input: Ultrasound image($\bar{I}1$), mammography image ($\bar{I}2$)
2. Output: Preprocessed fused image
3. Begin
4. For each I do
//Noise removal
5. Initialize wiener filter using eqn (1) for removing noise and blur
6. Initialize fuzzy membership function using eqn (3) for removing remaining noise
// Contrast Enhancement
7. Partition the images into equal size I_R, B_R, C_R
8. Estimate dynamic clip limit using eqn (8)
9. Execute bilinear interpolation process
10. Calculate new pixel $T_{p_{new}}$ using eqn (9)
11. Obtain contrast enhanced image
//Data Augmentation
12. Perform image flipping by providing mirror image
13. Perform rotation into right and left side based on $90^{\circ}, 180^{\circ}, and\ 270^{\circ}$
//Image fusion
14. Decompose the image using UDWT
15. Compute F_{LFS} using eqn (10)
16. Compute F_{HFS} using eqn (16)
17. Obtain inverse function using eqn (17)
18. Fused $\bar{I}1$ and $\bar{I}2$ by ICA using eqn (18)
19. End for
20. Return preprocessed fused image

ISSN: 2309-5288 (Print)
ISSN: 2309-6152 (Online)
CODEN: JCLMC4
Journal of Coastal Life Medicine

21. End

A. *Dual Agent-based Segmentation*

The fused image is effectively segmented to get the effective breast tumor severity results and achieves high accuracy classification with low complexity. The deep reinforcement learning algorithm called Dual Agent- Deep Q Network (DA-DQN) is adopted for fused image segmentation. Both the agents are trained effectively to produce accurate segmentation results. The first agent performs background subtraction for fused images by applying adaptive threshold method. With the background-subtracted images, the second agent initiates iterative search based on the already trained search policy for extracting the Region of Interest (ROI) by considering features such as *tumor density, blood flow, diameter, location, and size*. The tumors in the ROI are masked while the others (i.e., microcalcifications, and pectoral muscles) are left out. The action value function of DA-DQN is defined as follows,

$$Q^*(\mathfrak{S},\mathfrak{Z}) = \max_{\rho} \check{E}\left[\sum_{\mathfrak{S}=0}^{\infty} \delta^{\mathfrak{S}} R_{t+\mathfrak{S}} \,|\, \mathfrak{S}_t = \mathfrak{S}, \mathfrak{Z}_t = \mathfrak{Z}, \rho\right] \quad (19)$$

where eqn (19) represent the maximum number of rewards R_t with the aid of discount factorδ for every time step t that is achieved by the policy which is defined as follows,

$$\rho = P(\mathfrak{Z}|\mathfrak{S}) \quad (20)$$

where $\mathfrak{Z}$ represent the action and $\mathfrak{S}$ represent the state which creating a same observation. The correlation between the Q values and action values of the target is computed as follows,

$$R + \delta \max_{\mathfrak{Z}'} Q(\mathfrak{S}', \mathfrak{Z}') \quad (21)$$

where $\mathfrak{S}', and\ \mathfrak{Z}'$ represent the updated version of state and action respectively. The proposed DA-DQN has four hidden layers, three convolutional layers, and one fully connected layer. Here, all the layers are used ReLU activation function and the DA-DQN provide one output of every action. The loss function of the DA-DQN is shown as below,

$$L_i(\vartheta_i) = \check{E}_{(\mathfrak{S},\mathfrak{Z},R,\mathfrak{S}')\sim u(d)}\left[R + \delta \max_{\mathfrak{Z}'} Q(\mathfrak{S}', \mathfrak{Z}'; \vartheta_i^-) - Q(\mathfrak{S}, \mathfrak{Z}; \vartheta_i))^2\right] \quad (22)$$

where δ represent the agent discount factor, ϑ_i represent the DQN parameters for ith iteration,ϑ_i^- represent the DQN parameters for target calculation for ith iteration.ϑ_i^- represent the target network parameters which are updated with the parameters of DQN $(\vartheta_i)$for each step. The agent experiences $(\underset{\sim}{e}_t)$ are stored to perform experience relay.

$$\underset{\sim}{e}_t = (\mathfrak{S}_t, \mathfrak{Z}_t, R_t, \mathfrak{S}_{t+1}) \quad (23)$$

where $\mathfrak{S}_t$ represent the observed state in the period of t, and $\mathfrak{S}_t$ represent the received reward by an agent in t period. $\mathfrak{Z}_t$ represent the action taken by the agentsin period t, and $\mathfrak{S}_{t+1}$represent current resulting state in period $t+1$. The experiences of the agents are stored in the dataset at period t which is defined as follows,

$$data_t = [\underset{\sim}{e}(1), \underset{\sim}{e}(2), \ldots, \underset{\sim}{e}(t)] \quad (24)$$

Here, the Q learning updation is calculated by considering the experience$(\mathfrak{S}, \mathfrak{Z}, R, \mathfrak{S}')$ that are pinched randomly form the stored dataset $(data_t)$. In this way, agents perform background subtraction and segmentation using DA-DQN. The reason for adopting deep reinforcement learning is to reduce the run time complexity during segmentation and provide better results.

Pseudocode for Segmentation

1. Input: Preprocessed fused image
2. Output: Segmented image
3. Begin
4. Initialize replay memory $data_t$
5. Initialize Target Network action value using eqn (19)
6. Initialize two agents to learn the environment

ISSN: 2309-5288 (Print)
ISSN: 2309-6152 (Online)
CODEN: JCLMC4
Journal of Coastal Life Medicine

7. For episode=1, N do
8. Compute new state and calculate reward
9. Update state and action using eqn (21)
10. Extract features using convolutional layers
11. Agent takes action for image segmentation
12. End
13. Compute loss function using eqn (22)
14. Store agent experience using eqn (23)
15. End

B. *Breast Tumor Severity Classification*

The masked tumor part is provided to breast tumor severity classifier. The proposed work utilizes Enhanced U-Net (EU-Net) for breast tumor severity classification. The conventional U-Net have multi scale skip connections which are used computational sources and unwanted information, since the low-level features are used repeatedly at multiple scales. To overcome the problems of plain skip connections, we include spatial and channel attention gate which are integrated to the encoder and decoder architecture of the U-Net for improving classification performance. The proposed EU-Net algorithm includesfour modules namely, encoder, decoder, fusion, and classification which is shown in fig 5. The segmented image is sent to the encoder module as aninput. Then the features of decoder are calculated by multiplied the spatial channel attention gate with encoder features, and concatenate with the features of decoder. Then, the features of decoders are fused and send to the classification model to classify the image into three grades. Here, encoder extracts the features (f)like average intensity(i_a), degree of circularity(ε), sphericity(ω), intensity variance(φ), coarseness(α), and elongation$(\mathfrak{X})$which are extracted from the masked region of the tumor. The extracted features are fed to attention module to enhance the performance of EU-Net. The proposed spatial attention module includes two types of attention layers which addressed the spatial structure of the region, and enhanced the contextual information into the encoder, and reduced the gap between the decoder and encode features. The features from the encoder and decoder are shown as below,

$$E_f \in r^{c_1\times h\times w} \qquad (25)$$

$$D_f \in r^{c_2\times h\times w} \qquad (26)$$

$$f = \{i_a, \varepsilon, \omega, \varphi, \alpha, \mathfrak{X}\} \qquad (27)$$

wherec_1 and c_2 represent the count of channels and w, h represent the width and height of the feature map respectively. The spatialattention gate generates the spatial attention map and channel attention gate generates the channel attention map both are expressed as follows,

$$s_m \in r^{1\times h\times w} \qquad (28)$$

$$c_m \in r^{c1\times h\times w} \qquad (29)$$

The encoder features of the proposed EU-Net areexpressed as follows,

$$E_f{}' = E_f \otimes s_m(E_f, D_f) \otimes c_m(E_f, D_f) \qquad (30)$$

where $\otimes$ represent the element-based multiplication, and s_m attention map of spatial gate, and c_m represent the attention map of channel gate. The spatial attention gate implemented based on the relationship among spatial informations which focused on the region of salient features. Here, the spatial attention map collects the information form both decoder and encoder features which are applied to the pooling layer, and convolutional layer (1×1). The attention map is generated by concatenating the features from the convolutional layer. This process is done for each encoder and decoder for generating spatial attention map. The calculation of final spatial attention map is expressed as follows,

$$s_m^E(E_f) = f_1^{7\times 7}([AP(E_f), MP(E_f), f_1^{1\times 1}(E_f)]) \qquad (31)$$

$$= f_1^{7\times 7}([(E_f)_{AP}^s, (E_f)_{MP}^s, (E_f)_{1\times 1}^s]) \qquad (32)$$

$$s_m^D(D_f) = f_1^{7\times 7}([AP(D_f), MP(D_f), f_1^{1\times 1}(D_f)]) \qquad (33)$$

$$= f_1^{7\times 7}([(D_f)_{AP}^s, (D_f)_{MP}^s, (D_f)_{1\times 1}^s]) (34)$$

ISSN: 2309-5288 (Print)
ISSN: 2309-6152 (Online)
CODEN: JCLMC4
Journal of Coastal Life Medicine

$$s_m(E_f, D_f) = \partial(s_m^E(E_f) + s_m^D(D_f))$$ (35)

where AP is average pooling layer, MP is maximum pooling $f_x^{y\times y}$ represent the $y \times y$ convolutional layer, and x represent the filters and ∂ s a sigmoid function. Similarly, channel attention map generation is explained as follows, channel attention gate includes 1×1 convolutional layer which utilizes the squeezed features that generate the attention map of squeeze channel. The calculation of channel attention map is expressed as follows,

$$C_m^E(E_f) = f_n^{1\times1}[AP(E_f) + f_n^{1\times1}(MP(E_f))]$$ (36)

$$= f_n^{1\times1}((E_f)_{AP}^C, + f_n^{1\times1}((E_f)_{MP}^C))$$ (37)

$$C_m^D(D_f) = f_n^{1\times1}[AP(D_f) + f_n^{1\times1}(MP(D_f))]$$ (38)

$$= f_n^{1\times1}((E_f)_{AP}^C) + f_n^{1\times1}((D_f)_{AP}^C)$$ (39)

$$C_m(E_f, D_f) = \partial(f_{c1}^{1\times1}(C_m^E(E_f) + C_m^D(D_f)))$$ (40)

Hence, we utilize both advantages of channel and spatial gate. We have multiplied the input features into map of channel attention and spatial attention. The EU-Net achieved high classification and detection accuracy by utilizing both features map advantages. Finally, we classified the imaged into three severity grades such as grade 1- Normal tumor, grade 2- Moderate tumor, and grade 3- Severe tumor.

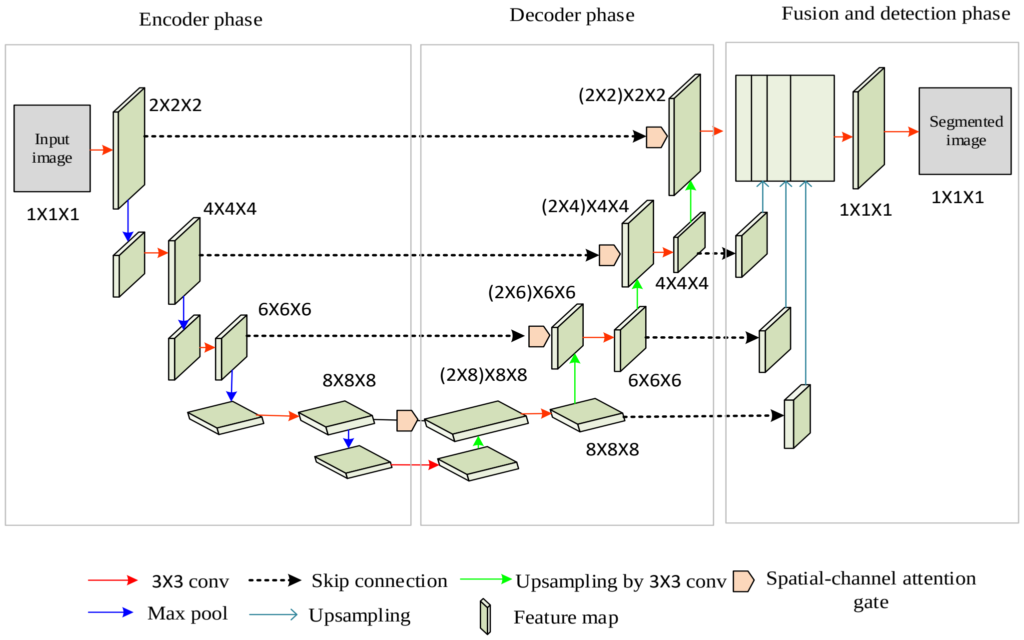

Fig.5 Architecture of Proposed EU-Net

5. Experimental Results

This section explained the experimental results of the proposed EU-Net model which also includes four sub sections which are dataset description, simulation setup, comparison analysis, and research summary. The detailed explanation of this section is described as follows.

A. *Dataset Description*

The BUS dataset includes ultrasound images of breast which was captured between 25- and 75-years old women. This dataset was created on 2018 which includes 600 female patients. The BUS dataset includes 780 images with 500*500-pixel images. additionally, this dataset classified the images into three classes such as normal, malignant, and benign. In this research, we have used only two classes for tumor grading such as malignant and benign.

The DDSM dataset is a public mammogram image dataset which includes three classes of datasets namely normal, malignant, and benign. In addition,

ISSN: 2309-5288 (Print)
ISSN: 2309-6152 (Online)
CODEN: JCLMC4
Journal of Coastal Life Medicine

it includes location of tumor, density rate of breast and abnormality types. It also includes ground truth images for both benign and malignant images. In this research, we have used two classes such as benign and malignant.

B. Simulation Setup

The simulation of the proposed EU-Net model is done by MATLAB R2020a. The MATLAB helps to enhance the simulation results performance. The proposed work algorithms are implemented in the MATLAB simulation tool. Table 1 illustrates the system specifications. The simulation of the proposed work performed the following processes such as preprocessing, dual agent-based segmentation, and breast tumor severity classification. Fig. 6 represent the simulation result of proposed EU-Net model. 6(a) represent the noise removed image of ultrasound and 6(b) represents the contrast enhanced image of ultrasound 6(c) represent the noise removed image of mammograms and 6(b) represents the contrast enhanced image of mammograms, and 6(e) represent the fused image of ultrasound and mammograms.

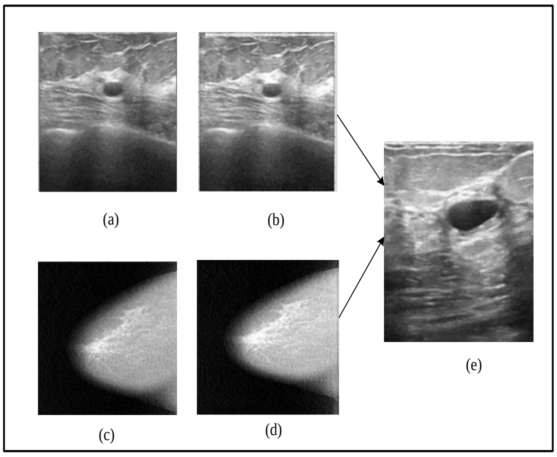

Fig.6 Simulation Results of Proposed EU-Net Model

Table.1System Specifications

Specifications of hardware	Central Processing Unit	3.00GHz
	RAM	6 GB
	Storage of hard disk	1 TB
	Processor	Intel (R) core (TM) i5-4590S
Specifications of software	MATLAB	R2020a
	OS	Windows 10

B.Comparative analysis

This section explains the comparative analysis of the proposed EU-Net model which is compared with two existing works namely MSF-UNet [28], and BCD [30]. The performance of the proposed work is evaluated by various performance metrics which are explained as follows,

a. Impact of Accuracy

This metric is used to calculate the accuracy of the proposed EU-Net model. The accuracy is calculated as the ratio between sum of positive and negative samples and overall samples. The mathematical representation of accuracy is defined as follows,

$$\mathbb{A} = \frac{T_P + T_N}{T_P + T_N + F_P + F_N} \qquad (41)$$

where T_P represent true positive, T_N is true negative, F_P represent false positive, and F_N false negative.

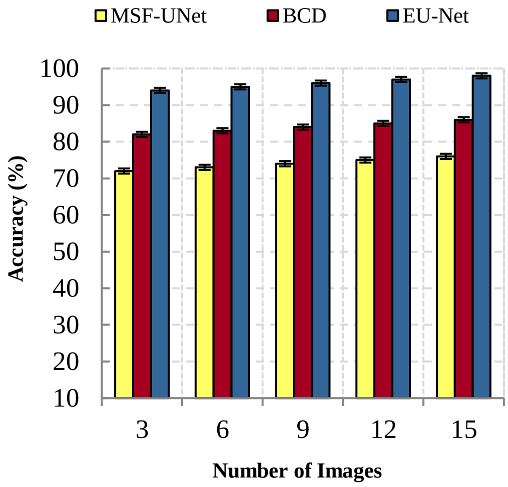

Fig.7 Accuracy vs. Number of Images

Fig 7 represents the comparison of accuracy for both proposed and existing works with respect to number of images. The comparison result shows that the proposed EU-Net model achieved high

ISSN: 2309-5288 (Print)
ISSN: 2309-6152 (Online)
CODEN: JCLMC4
Journal of Coastal Life Medicine

accuracy compared to other two existing works. The accuracy is gradually increased with the increasing number of images. Here, preprocessing includes three steps such as noise removal, contrast enhancement, and data augmentation which improve the detection accuracy by reducing noise, illumination and blurriness, but the existing MSF-Net model does not perform noise removal which reduces the accuracy due to poor image quality. The existing BCD works perform noise removal, and contrast enhancement as preprocessing, but the presence of blurriness leads to poor image quality that also reduces the accuracy of the breast cancer detection. The proposed EU-Net model achieves 22% higher than MSF-UNet and 12% higher than BCD.

b. Impact of Precision

This metric is used to calculate the positive prediction value of the proposed work. The calculation of precision is defined as the ratio between true positive rate and sum of true and false positive rates which is expressed as below,

$$\mathbb{P} = \frac{T_P}{T_P + T_N} \qquad (42)$$

Fig 8represents the comparison of precision for both proposed and existing works with respect to number of images. The comparison result shows that the proposed EU-Net achieves high precision when compared to other two existing works. The proposed work performed three level of preprocessing such as noise removal, contrast enhancement and data augmentation which increases the detection accuracy. In addition, we have proposed reinforcement learning algorithm for segmentation which learns the environment and takes actions based on the current status of the environment. For increasing segmentation accuracy, we consider many features for segmentation such as tumor density, blood flow, location, diameter, and size. But the existing BCD work consider limited features (i.e median, entropy, and mean) for segmentation which reduces segmentation accuracy, therefore it increases the false positive rate. The existing MSF-UNet also takes two features (i.e edge and texture) for segmentation which increases misclassification results. The proposed EU-Net achieves 18% higher than BCD and 22% higher than MSF-UNet.

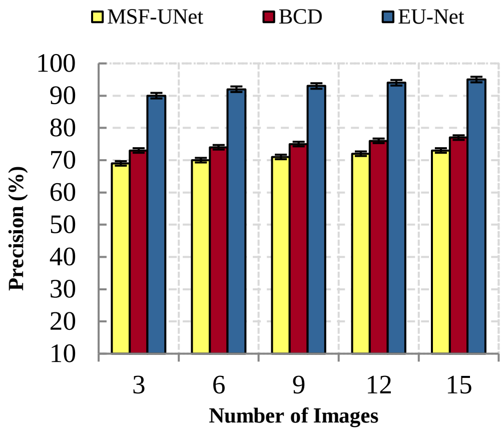

Fig.8Precision vs Number of Images

c. Impact of Recall

Recall is a metric which is defined as the true positive values are divided by the total number of samples which fit to the positive classes. The mathematical expression of recall is defined as follows,

$$\mathbb{R} = \frac{T_P}{T_P + F_N} \qquad (43)$$

Fig 9 represents the comparison of recall for both proposed and existing methods. The recall is increases gradually with respect to the number of images. The comparison result shows that the proposed work achieved high recall compared to existing works. The proposed work performed three stage preprocessing which increases the accuracy and recall of the proposed work. Here, segmentation is done by reinforcement learning algorithm namely DA-DQN with many features. To increases the classification performance the proposed EU-Net model used enhanced U-Net algorithm which classified the severity of the breast tumors. The existing BCD model used machine learning algorithm for classifying the breast cancer which reduces the accuracy because of trained smaller dataset compared to deep learning. The existing MSF-UNet model performed segmentation of breast region by considering texture and edge features, however it leads to poor recall due to considering limited

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CODEN: JCLMC4
Journal of Coastal Life Medicine

features for segmenting breast region. The proposed EU-Net achieves 14.6% higher than BCD model, and 19.6% higher than MSF-UNet model.

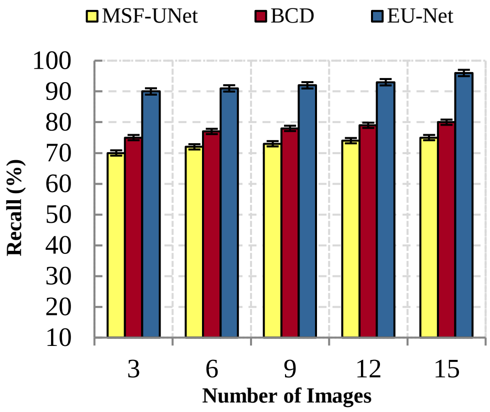

Fig.9Recall vs Number of Images

d. Impact of F-Measure

This metric is defined as the harmonic mean of the recall and precision the mathematical representation of the proposed EU-Net is defined as follows,

$$\mathbb{F} = 2.\frac{\mathbb{P} \times \mathbb{R}}{\mathbb{P} + \mathbb{R}} \quad (44)$$

where $\mathbb{F}$ represent F-measure and $\mathbb{P}$ represent precision and $\mathbb{R}$ is a recall. Fig 10 represents the comparison of f-measure for both existing and proposed work with respect to number of images. The figure shows that the proposed work achieves better f-measure value compared to existing works. The f-measure value is increases with the increasing number of images. The proposed work achieves high precision and recall; hence it also has high f-measure. The reason of achieving high f-measure is three stage preprocessing which reduces noise, illumination, blurriness and utilize multi-dimensional information of both ultrasound and mammograms images. In addition, this research uses the fused information of mammograms and ultrasound images which increases the accuracy, precision, recall, and f-measure. Additionally, this research takes multiple features for both segmentation and severity grading which also increases the detection results and f-measure. The proposed EU-Net achieves 20% higher than BCD model and 23% higher than MSF-UNet model.

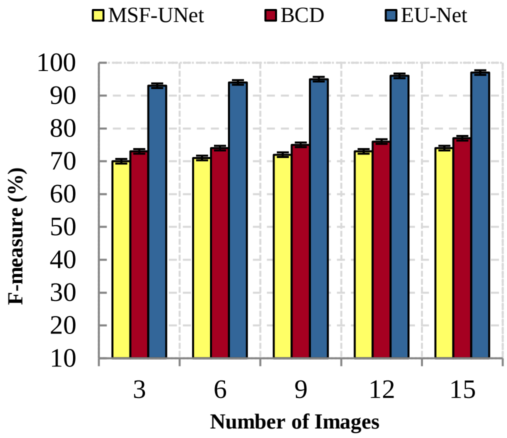

Fig.10 F-Measure vs Number of Images

e. Impact of Computation Time

The computation time is defined as that the volume of time taken for computing all the process in breast tumor detection. If the work has low computation time, then it achieves good performance.

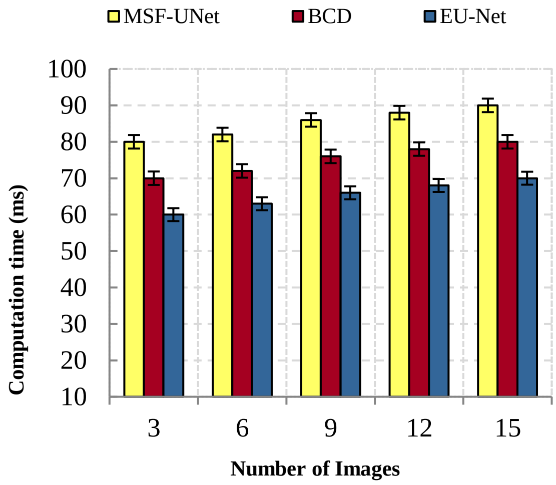

Fig.11 Computation time vs Number of Images

Fig 11 represent the comparison of computation time for both proposed and existing works with respect to number of images. The computation time is increased with respect to increasing number of images. The figures proved that the proposed EU-Net model achieved less computation time compared to MSF-UNet and BCD models. The

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CODEN: JCLMC4
Journal of Coastal Life Medicine

proposed work takes fast processing algorithms to reduce computation time. Initially, we take hybrid filtering algorithm to reduce noises in the images which provides noise removed images with minimum time because of its processing speed. For segmentation, we have used two agent based reinforcement learning algorithm which provides a segmentation results with minimum amount of time due to learn the environment by two agents. Finally, severity classification is done by EU-Net which increases the processing speed by integrating spatial channel attention gate which reduces the delay and increases the performance of the proposed work. The existing MSF-UNet model used multi scale dilated convolution which takes much time for segmenting the breast region due to its slow processing which increases computation time. The existing BCD model used wavelet transform model for preprocessing which has computationally intensive nature which automatically increases the computation time. Additionally, it used machine learning algorithm for classification it takes much time for training which also increases the computation time. The proposed EU-Net model achieves 9.8ms lesser than BCD and 19.8ms lesser than MSF-UNet model.

f. Impact of ROC Curve

ROC stands for received operating curve which shows the graphical representation between false positive rate and true positive rate. The ROC curve represents the accuracy of the proposed EU-Net model. Fig 12 depicts the relationship between false positive rate and true positive rate for both proposed and existing work. The comparison shows that the proposed work achieved highest true positive rate with respect to false positive rate compared to existing works. The proposed work achieves 0.95 true positive rate, and BCD achieves 0.8 true positive rate and MSF-UNet achieves 0.7 true positive rate. The higher result of proposed EU-Net is achieved by performing three stage preprocssing and image fusion, reinforcement-based segmentation and severity classification of breast tumors.

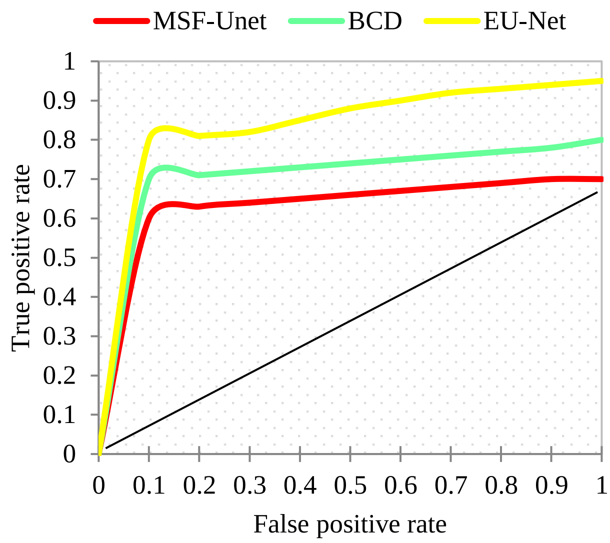

Fig.12 False Positive Rate vs True Positive Rate

C. Research Summary

This section summarizes the overall performance of the proposed EU-Net model. The results section shows that the proposed work achieves superior performance in terms of accuracy, precision, recall, f-measure, computation time and ROC curve which are shown in fig7 - fig 12. These results are achieved by performing three stage preprocessing, RL based segmentation and severity classification using EU-Net. Table 2 represent the comparison results of proposed and existing approaches which provides the average numerical values of the performance metrics. The research highlights are described as follows,

- For reducing the noise and improve the quality of input images, we perform three-stage pre-processing in which noises are removed by hybrid filters, image quality is enhanced by CLAHE, and data augmentation is performed to increase the data size class.
- For achieving better segmentation results, we perform dual DRL-based segmentation by using DA-DQN which reduces the run time complexity and provided better segmentation results.
- For improving the classification accuracy, we perform EU-Net-based classification in which redundant features are removed by

attention module and provide high classification accuracy with less complexity.

Table.2 Numerical Analysis of Proposed and Existing Works

Performance metrics	Scenario	Existing vs. Proposed systems		
		MSF-UNet	BCD	EU-Net
Accuracy (%)	No. of Images	74	84	96
Precision	No. of Images	71	75	92.8
Recall	No. of Images	72.8	77.8	92.4
F-Measure	No. of Images	72	75	97
Computation time (ms)	No. of Images	78	75.2	65.4
ROC curve	No. of Images	0.7	0.8	0 95

6. Conclusion and Future work

The early and accurate detection of breast tumors reduces the mortality. In this research, we proposed EU-Net model for breast tumor severity classification using fusion of mammograms and ultrasound images. Initially, preprocessing is performed to reduce noise, illumination, and blurriness of both ultrasound and mammograms images. For that, this research performed hybrid filter-based noise removal, A-CLACH based contrast enhancement, and UDWT-ICA based image fusion which improves the quality of the image and performance of severity grading. The preprocessed fused images are forward to segmentation, here DA-DQN algorithm is proposed for segmentation which segments the tumor by considering many features (i.e tumor density, blood flow, diameter, location, and size) and suppressing background information of image. Finally, tumor severity classification is done by EU-Net which extract the features (i.e average intensity, degree of circularity, sphericity, intensity variance, coarseness, and elongation) from the segmented region for classifying the tumors into three classes such as grade 1-normal, grade 2-moderate, and grade-3 severe tumor. Finally, the proposed EU-Net achieves better performance in terms of accuracy, precision, recall, f-measure, computation time, and ROC curve. In future, we planned to propose ensemble learning approach to increase classification accuracy.

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