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A unique YOLO-based gated attention deep convolution network-Lichtenberg optimization algorithm model for a precise breast cancer segmentation and classification

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ABSTRACT

A novel you only look once (YOLO)-based gated attention deep convolution network (GADCN) classification algorithm is developed and utilized in this present study for the detection of breast cancer. In this framework, contrast enhancement-based histogram equalization is applied initially to produce the normalized breast image with reduced noise artifacts. Then, the breast region is accurately segmented from the preprocessed images with low complexity and segmentation error using the YOLO-based attention network model. To diagnose breast cancer with better accuracy, the GADCN model is used to predict the exact class of image (*i.e.*, benign or malignant). During classification, the activation function is optimally computed with the use of the Lichtenberg optimization algorithm (LOA). It aids in achieving improved classification performance with little complexity in training and assessment. The significance of the present study includes the use of a unique, YOLO-based GADCN-LOA model that helps in the prediction of breast cancer with higher accuracy. It was observed that the model exhibited 99% accuracy for the datasets utilized. In addition, the selected model outperforms well with sensitivity, specificity, precision, and F1-score. Hence the proposed model could be exploited for the diagnosis of breast cancer at an early stage to enable preventive care.

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1. INTRODUCTION

According to the World Health Organization (WHO) report, breast cancer [1], [2] is regarded as the second biggest cause of morbidity for women, and nearly 8.2 million people die each year from cancer and predicts the statistic will grow to 27 million by 2030 [3]. Therefore, early diagnosis, timely and accurate detection, and proactive prevention are essential elements in lowering the mortality rate for women [4], [5]. Further, it is essential to predict the disease at an early stage so that the treatment can be given well in advance. For locating and precisely identifying the tumor-affected area, many imaging modalities are used. Medical professionals often use mammography images in tandem with other imaging methods to diagnose and treat patients with accuracy [6]–[8]. Various medical image processing techniques have been employed in the existing research with the intent of detecting breast cancers from mammograms [9], [10]. Computer-aided diagnosis (CAD) [10], [11] systems require the detection, segmentation, and classification of medical images to assist radiologists in exactly locating the cancer-affected breast region. As a result, a precise method of breast cancer identification and categorization is suggested for mammography screening. An automated CAD-based diagnosis tool [2], [12], [13] has recently been used in certain existing studies with deep learning techniques.

Deep learning is the most practical technique widely used for identifying abnormalities from medical images in the real world. Moreover, the standard image processing stages are involved in the automated system that enables the deep learning model to perform well. Substantial hierarchical feature maps can be produced by deep learning algorithms from the identical mammogram breast image. An ample true positive rate and disease diagnosis results are dependent upon the accurate diagnosis of suspicious breast lesions [14]–[16], which come in a wide variety of shapes, textures, and positions that make the detection challenging. More specifically, a number of scientists have used convolutional neural network (CNN) models, including Inception ResNet-V2, Inception-V3, VGG16 and 19, GoogleNet, ResNet-18, 50, and 101, to diagnose breast cancer. Similar to this, the application of artificial intelligence has been crucial in the diagnosis of breast tumors through the use of several machine learning algorithms. Although various methods try to forecast the tumor and categorize it as benign or malignant, the current approaches have a number of shortcomings. Using widely accessible breast image datasets, the current study aims to create a novel you only look once (YOLO)-based gated attention deep convolution network (GADCN)-Lichtenberg optimization algorithm (LOA) model for the prediction of breast cancer in order to get beyond the restrictions.

The goal of the proposed research project is to create a new segmentation and classification model based on deep learning for precise breast cancer detection. Below is the suggested framework for the current investigation:

a. To create the normalized image, a contrast limited adaptive histogram equalization (CLAHE)-based image preprocessing model has been used, which carries out histogram equalization and contrast enhancement procedures.
b. The YOLO-based attention network model is implemented to accurately segment the breast region from the preprocessed images with low complexity and segmentation error.
c. The GADCN model is applied to predict the accurate class of image (*i.e.,* benign or malignant) for a proper abnormality identification from the breast image.
d. To determine the ideal value for calculating the activation function utilized in the GADCN model, the LOA is utilized. Low training and testing complexity contributes to better categorization performance.
e. This study uses a number of common and well-known breast image datasets for system implementation and performance validation, including the digital database for screening mammography (DDSM), mammographic image analysis society (MIAS), INBreast, Wisconsin diagnostic breast cancer (WDBC), and Wisconsin breast cancer dataset (WBCD).

Here, an exhaustive literature review is carried out to examine various methodologies used in the bio-medical field for the identification of abnormalities from the breast image. Through their segmentation and classification procedures, it investigates the advantages and difficulties associated with the current models. Hamed *et al.* [17] investigated the recent learning-based classification approaches for predicting abnormalities from the breast image. The authors intend to identify the premature signs of breast cancer from the mammogram images by developing a CAD model. Khan *et al.* [18] utilized a transfer learning mechanism for an accurate determination and categorization of breast abnormalities from mammogram images. In this framework, a combination of multiple CNN architectures is employed to obtain fast and accurate detection results. Soulami *et al.* [19] implemented a UNet-based segmentation model for developing an automated breast cancer detection system. Here, the pixel-to-pixel classification is performed to obtain accurate detection results.

Jabeen *et al.* [20] deployed a probability-based deep learning architecture model for the identification of abnormalities from the ultrasound breast images. This framework includes the operations of data augmentation, pre-training, feature extraction, optimization, and prediction. Here, the probabilistic method is utilized to merge the best-chosen characteristics. Shahidi *et al.* [21] presented a comparison study to examine various classification methodologies used in the field of medical imaging. This study set out to show how deep-learning techniques could be used to categorize histological images of breast cancer. The difficulties in classifying breast cancer pathology images were noted, and possible solutions were considered in this study.

Sunny *et al.* [22] carried out a comparison study to verify the effectiveness of the common machine learning classifiers. To use the classification algorithms, the dataset was split into training and testing phases. The method that yields the best results will be used on the website's backend, and the predicted outcome will label the tumor as either benign or malignant. Artificial intelligence (AI) applications such as machine learning let computers learn from their past actions and become better as time passes without explicit programming. Machine learning is primarily concerned with software applications that retrieve available data and use it to gain knowledge by themselves. Krithika and Geetha [23] did a systematic review to look at various methods to locate cancer in breast tissue. Additionally, it looks into a few of the well-known machine learning models employed in the conventional systems are listed in Table 1.

Table 1. List of conventional classification models

Ref	Classification techniques	Merits	Challenges
[24]	Support vector machine (SVM)	It works well in high dimensional space and efficient memory utilization.	It is not capable of handling huge datasets and falls in local optima.
[25]	Decision tree (DT)	Easy to understand, and it can handle multi-output problems.	A small change in the tree structure could affect the performance of the entire classification, and the prediction highly depends on the selection attributes.
[26]	Fuzzy logic (FL)	Better robustness, and capability of handling imprecise data.	Inaccurate predictions, and not suited for all applications.
[27]	Deep learning (DL)	Works well for large dimensional data, and high accuracy.	Requires complex mathematical operations to predict the desired result, and lack of interpretability.
[28]	Naïve Bayes (NB)	High processing speed, and performs well for large-size data.	Overfitting, and complexity.

2. METHOD

This section provides a complete explanation of the proposed YOLO-based GADCN-LOA breast cancer detection system. This paper's key contribution is the development of an innovative CAD framework for the precise segmentation and classification of tumors from the input mammography breast images. The proposed YOLO-based GADCN-LOA framework's flow is portrayed in Figure 1, which encompasses the following operations: i) Contrast enhancement and equalization, ii) YOLO-based attention network model for segmentation, iii) GADCN model for disease classification, and iv) LOA for activation function estimation.

The input breast image obtained from the given dataset is initially preprocessed with the use of the CLAHE model, where the image enhancement, histogram equalization, noise removal, and normalization operations are carried out [29]. This kind of preprocessing algorithm helps to reduce the classification error while minimizing the training and testing time. Then, a novel YOLO-based attention network model is utilized to segment the breast region from the preprocessed image with a reduced over-segmentation rate. To accurately predict the healthy and cancer-affected images with high precision and detection accuracy, the GADCN-based classification algorithm is used in this system [30]. During classification, the activation function is estimated based on the optimal solution obtained from the LOA. The major merits of the proposed YOLO-based GADCN-LOA framework are reduced classification error, improved accuracy, low system complexity, minimized time consumption, and reduced over-segmentation.

2.1. Pre-processing

It is the initial stage of the proposed framework, where the image filtering and normalization processes are carried out to generate the contrast-enhanced quality output image. A technique known as image enhancement is a way to treat an image so that the outcome is significantly more appropriate for a given application than the original image. The numerous forms of noise present in the unprocessed images gathered from the scanner port and websites make them unsuitable for immediate processing. Consequently, it needs to be transformed before being examined. An important step in image processing is scaling an image to change its pixel size. Here, the CLAHE preprocessing model is used to generate the quality-enhanced breast image with reduced noise. When compared to the other preprocessing models, the key benefits of using CLAHE are simple to implement, enhanced image contrast, and better visibility. During this operation, the image normalization, and histogram equalization processes are carried out. After obtaining the input image, the normalization is performed based on the minimum and maximum values as represented in the following model:

$$I^{norm} = (I^{inp} - I^{min}) * \sum_{x=1}^{m} \sum_{y=1}^{n} \frac{I^{inp}(x,y)}{I^{max} - I^{min}} + N_o \tag{1}$$

where N_o is the total number of image sizes, $I^{inp}(x, y)$ is the image pixel at each coordinate, m & n are the number of rows and columns of the image, I^{inp} denotes the input image, I^{min} denotes the minimum value of the input image, and I^{max} denotes the maximum value of the input image. Thus, as illustrated below, the histogram equalization is used.

$$h^t = histogram(I^{norm}) \quad (2)$$

where h^t represents the histogram-transformed image. Finally, the quality-enhanced image is obtained as shown in the following form:

$$C_L = \{h^t(x,y) | \forall (x,y) \in I^{inp}\} \quad (3)$$

where C_L is the enhanced breast image, I^{inp} denotes the input image, and x, y are the pixel coordinates. The output quality enhanced image is used for segmentation and classification operations.

Figure 1. Flowchart of the proposed YOLO-based GADCN-LOA breast cancer detection system

2.2. YOLO based attention network segmentation

After image preprocessing, the YOLO-based attention network segmentation model is used to segment the breast image from the quality-enhanced image. In general, the different types of threshold-based, encoding-based, and deep architecture-based segmentation models are implemented in the existing studies for breast cancer diagnosis. However, most of the techniques have the main drawbacks of over-segmentation, high designing complexity, and increased time consumption. Therefore, the proposed work intends to use a sophisticated deep segmentation model for predicting cancer in breasts. The attention mechanism makes use of the human capacity for selective attention. In particular, a person might focus on the areas of interest while quickly scanning the entire image. The model might then automatically focus on crucial sequence features, improving the ability to handle sequence data without increasing the cost of computation. Following that, detailed information about specific regions is acquired and unnecessary information is suppressed. In the proposed system, the lightweight YOLO-based attention network is specifically implemented to perform segmentation with minimized computational complexity and time consumption. The novel concept of this model is, that a boundary loss function is computed to improve the disease prediction rate. Moreover, the proposed segmentation architecture model comprises the following layers: i) input layer, ii) backbone layer, iii) feature pyramid layer (FPL), iv) path aggregation layer (PAL), and v) prediction layer

The input layer is mainly used to gather the input image data for enhancement. Then, the backbone layer comprises the slice module that helps to improve the process of computation with reduced speed. Moreover, the FPL and PAL are used to perform the fusion and, complementation of high-level features and low-level features respectively. Finally, the prediction layer is used to generate the output class according to the boundary loss function. After getting the enhanced image C_L from the previous stage, the layer initialization is performed at first. Then, the dynamic anchor localization is performed with the use of a backbone layer, where the matching degree is estimated based on the spatial matching information, feature placement capability, and regression ambiguity. Here, the localization capacity is measured according to the regression ambiguity, and is represented in the following model:

$$D^M = \varphi * S_\alpha + (1-\varphi) * \oint_\alpha - \rho^\vartheta \tag{4}$$

where φ & ϑ are the hyperparameters used to weigh the influence of different data, S_α is the spatial matching information, $\oint_\alpha$ indicates the feature placement capability for input data, and ρ is a penalty term. After that, an intersection over union (IoU) is estimated before and after regression ambiguity as represented in the following model:

$$\rho = |S_\alpha - \oint_\alpha| \tag{5}$$

Moreover, the hyperparameter is computed according to the precise adjustment schedule as shown in the following model:

$$\varphi(t) = \begin{cases} 1, & t < 0.1 \\ 5 * (\varphi_0 - 1) * t + (1.5 - 0.5 * \varphi_0) & 0.1 \le t < 0.3 \\ \varphi_0 & t \ge 0.3 \end{cases} \tag{6}$$

$$t = \frac{i^t}{M^I} \tag{7}$$

where i^t indicates the current iteration, M^I is the total number of iterations, and φ_0 represents the previous weighting factor of each iteration. Furthermore, the attention mechanism is implemented with the perceptron model, where the spatial attention is computed to improve the network's sensitivity to identify the defected areas. During this process, the channel attention weight is computed as shown in (8):

$$C^A(f) = \delta * \left(P_l(q_{avg}) + P_l(q_{max})\right) \tag{8}$$

Then, the spatial attention weight is estimated by using the following model:

$$S^A(f) = \delta * \left(conv(q_{avg} * q_{max})\right) \tag{9}$$

where, $P_l(.)$ represents the perceptron layer, $conv(.)$ represents the convolutional operation with the kernel size 7*7, q_{avg}& q_{max} indicates the channel dimension of average and maximum features, and δ denotes the channel attention parameter. Furthermore, the final attention mechanism is applied to make an appropriate segmentation decision as illustrated in (10):

$$Q' = C^A(f) \otimes f \tag{10}$$

$$Q'' = S^A(f) \otimes Q' \tag{11}$$

Consequently, the fusion model is applied to fuse the features for obtaining an accurate defect recognition probability. The novel concept of this model is to compute the boundary loss function according to the ground truth bounding box as represented in the following model:

$$G_{IoU}(X,Y) = IoU(X,Y) - \frac{|Z|-|X \cup Y|}{|Z|} \tag{12}$$

$$\mathfrak{L}_{G_{IoU}} = 1 - G_{IoU}(X,Y) = 1 - IoU(X,Y) + \frac{|Z|-|X \cup Y|}{|Z|} \tag{13}$$

where Z is the smallest box containing X and Y, G_{IoU} denotes the disjoint situation of X and Y in IoU that has similar scale-invariance characteristics. Moreover, the direction is gradually computed based on the distance between two minor components, and D_{IoU} can effectively reduce the distance between two target boxes, hence it converges the speed much faster. Then, the parameter D_{IoU} is computed by using the following model:

$$D_{IoU} = IoU - \frac{E^2(p,p^{gt})}{d_c} \tag{14}$$

$$\mathfrak{L}_{D_{IoU}} = 1 - D_{IoU} = 1 - IoU + \frac{E^2(p,p^{gt})}{d_c} \tag{15}$$

where, p and p^{gt} indicate the prediction's primary points box p and ground-truth box p^{gt}, respectively, d_c indicates the square of the minimal bounding box's Z diagonal length, and E^2 denotes the Euclidean distance. In the following model, there are two boxes in both the horizontal and vertical orientations:

$$IoU = IoU\text{-} \left[\frac{E^2(p,p^{gt})}{d_c} + \omega\tau\right] \tag{16}$$

$$\mathfrak{L}_{C_{IoU}} = 1 - IoU + \left[\frac{E^2(p,p^{gt})}{d_c} + \omega\tau\right] \tag{17}$$

where ω is the weight parameter and τ is used to measure the similarity of the aspect ratio. Finally, the process has been iterated until reaching the lowest intersection over union (IoU), which returns the segmented image as the result.

2.3. Gated adaptive deep convolutional network

After segmentation, the novel GADCN-based classification algorithm is implemented to accurately predict the disease from the segmented image. Traditionally, various deep-learning algorithms are implemented for breast cancer detection and class identification. However, most of the mechanisms have major problems in terms of increased computational complexity, mis-prediction rate, and high system complexity. Therefore, the proposed work aims to use a novel GADCN classification algorithm for breast cancer diagnosis, Lichtenberg optimization algorithm is employed to compute the activation function for enhancing prediction accuracy. As a result of studying the channel attention mechanism, this system uses a special attention module to promote an adaptive feature fusion that incorporates the channel relevance description into the standard gated attention (GA) module. The gated mechanism is then used to perform adaptive feature fusion by the gated channel attention coefficients, allowing the gated mechanism to take into account all of the weights supplied to classification feature maps and use the fully connected sub-networks weights to explain the significance across channels. It does this by obtaining the statistical parameters of an adaptive gated channel using global pooling and a fully connected sub-network. After obtaining the segmented image I_{seg}, the feature map is constructed at first based on the convolution operation as shown in (18):

$$Fea_m = conv(I_{seg}) \tag{18}$$

where $conv(.)$ indicates the convolutional operation. Then, the adaptive weight is estimated using the feature map of the segmented pixel as represented in the following model:

$$\overline{I_{\mathfrak{w}}} = \delta * Fea_m^i + (1-\delta)\sum_{i\in D_k} \mathfrak{w}_i \overline{I_{\mathfrak{w}}}^i \quad (19)$$

where the segmented pixel's Fea_m^i feature map, δ, which ranges from 0 to 1, is the coefficient of Fea_m^i. The weighted average of the characteristics of pixels within the same sup-pixel is represented by the function $\sum_{i\in D_k} \mathfrak{w}_i \overline{I_{\mathfrak{w}}}^i$, with $(1-\delta)$ as the corresponding coefficient. Here, the feature distance between the pair of pixels is used to estimate the adaptive weight that corresponds to the nearby pixel of the segmented image I_{seg}, as illustrated in the model that follows.

$$\mathfrak{w}_i = \exp\left(-\frac{\left|\overline{I_{\mathfrak{w}}}^i - \overline{I_{\mathfrak{w}}}^j\right|}{\sigma^2}\right) \quad (20)$$

where $exp\,(.)$ indicates the exponent function, $\left|\overline{I_{\mathfrak{w}}}^i - \overline{I_{\mathfrak{w}}}^j\right|$ is the absolute value of the difference between features of i^{th} and j^{th} pixel. σ^2 refers to the variance of the intensity features of pixels within the adjacent pixel. Moreover, the global pooling operation is performed in the pooling layer as represented in (21):

$$[\mathfrak{f}_1, \mathfrak{f}_2, \dots, \mathfrak{f}_r] = globalpooling(g_C^1, g_C^2, \dots, g_C^r) \quad (21)$$

where g_C^r represents the channel matrix of r number of features and $\mathfrak{f}_r$ is the corresponding feature obtained by global pooling. Consequently, the function named rectified linear units (ReLU) is applied as the active function of the first fully connected layer to make the parameters of GADCN as illustrated in the following model:

$$z_i = ReLU(\mathfrak{w}_i^T * Fea_m^i + \mathfrak{b}_i) \quad (22)$$

where $\mathfrak{b}_i$ indicates the bias of the neuron. Then, the output values are refined by using the sigmoid function, which indicates the gated attention coefficient value ranging as (0, 1):

$$\lambda = sigm\left(\mathfrak{w}_i^T(Y_{tg}) * Fea_m^i(Y_{tg}) + \mathfrak{b}_i(Y_{tg})\right) \quad (23)$$

where Y_{tg} is the output of lightweight feature optimizing (LFO). Moreover, the feature fusion is performed by the gated attention mechanism as represented in the following model:

$$x_n^{fuse} = \lambda \otimes \mathfrak{f}_1 + \dots + (1-\lambda) \otimes \mathfrak{f}_r \quad (24)$$

Finally, the classified label is predicted as the output with the cost function as shown in (25):

$$L = -\frac{1}{N}\sum_{m=1}^{N}\sum_{k=1}^{H}(z_i = k)\left\{\frac{e^{x_n^{fuse}}}{\sum_{k=1}^{H} e^{x_n^{fuse}}(m)}\right\} \quad (25)$$

where N is the number of values in feature fusion and H number of classes.

2.4. Lichtenberg optimization algorithm

During classification, the activation function is optimally computed based on the best optimal value obtained from the LOA. When compared to the traditional optimization techniques, the LOA provides an improved performance outcome, which helps to obtain the maximum disease prediction accuracy. In this model, the objective function in the searching space at first with the upper and lower bound values. Similarly, the maximum number of iterations and number of populations are also initialized. Then, the random scaling and rotation operations are carried out to estimate the fitness value for the given problem.

3. RESULTS AND DISCUSSION

The performance and results of the YOLO-based GADCN-LOA mechanism for the breast cancer diagnosis obtained using popular benchmark datasets is described in this section. The evaluation measures such as accuracy, sensitivity, specificity, precision and F1-score are analyzed to validate the proposed model. The current study utilizes the public and most popular datasets for system validation and analysis [31] and are represented in Table 2.

With linked ground truth of mass regions, the DDSM database has roughly 2,620 cases of cancer, benign, and normal breast images. Decompressed to a size of 5000×3000 pixels, the selected pictures for the CBIS-DDSM dataset have been translated into DICOM format. The MIAS database contains 322 digital mammography images, each measuring 1,024 by 1,024 pixels and in PGM format. The entire INBreast database contains 410 photographs, representing benign, malignant, and normal states. It contains 112 masses in total, all of which are linked to accurate ground truth outlines created by professionals. The images in this database are recorded in the DICOM file format and range in size from 2560×3328 pixels to 3328×4084 pixels, depending on the size of the patient's breast. Figure 2(a) to 2(f) display the sample input and output breast images, which include the input photos, ground truth images, preprocessed outputs, clustered outputs, binary outputs, and output images with tumors detected.

Table 2. Datasets used in this study

Datasets	Description
Set 1	DDSM
Set 2	INBreast
Set 3	MIAS
Set 4	WDBC
Set 5	WBCD

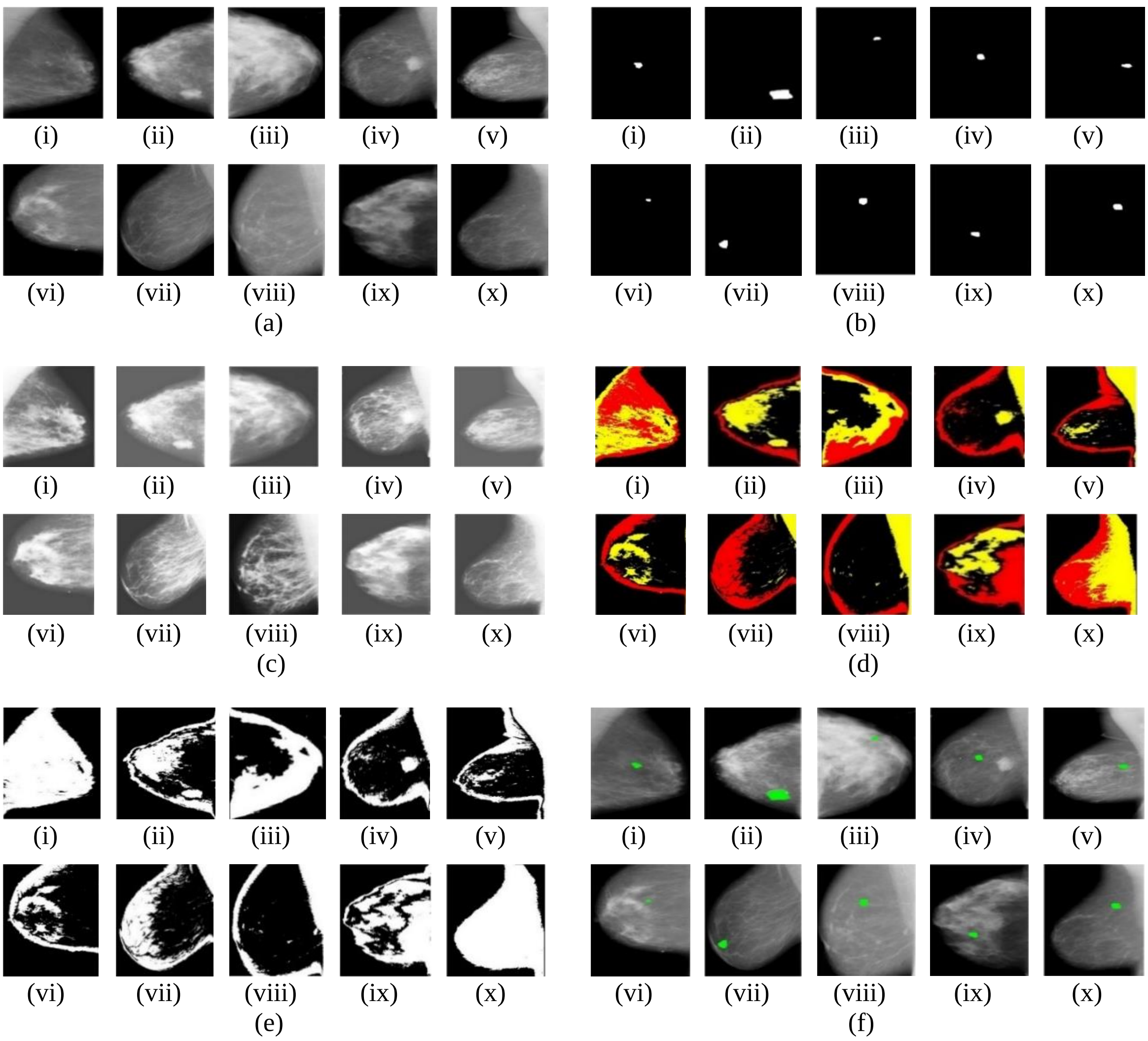

Figure 2. Breast tumor detection stages (a) input breast images, (b) ground truth breast images, (c) preprocessed breast images, (d) clustered output images, (e) binary output images, and (f) tumor detected images

Moreover, the performance measures used to assess the results are computed by using the following models:

$$Accuracy = \frac{Tp+Tn}{Tp+Fp+Tn+Fn} \tag{26}$$

$$Sensitivity\ or\ Recall = \frac{Tp}{Tp+Fn} \tag{27}$$

$$Specificity = \frac{Tn}{Tn+Fp} \tag{28}$$

$$Precision = \frac{Tp}{Tp+Fp} \tag{29}$$

$$F1-score = \frac{2\times Precision\times Recall}{Precision+Recall} \tag{30}$$

where, Tp is true positives, Tn is true negative, Fp is false positive, and Fn is false negative. By using the DDSM, INBreast, and MIAS datasets, Figure 3 verifies the receiver operating characteristics (ROC) of the proposed YOLO-based GADCN-LOA model.

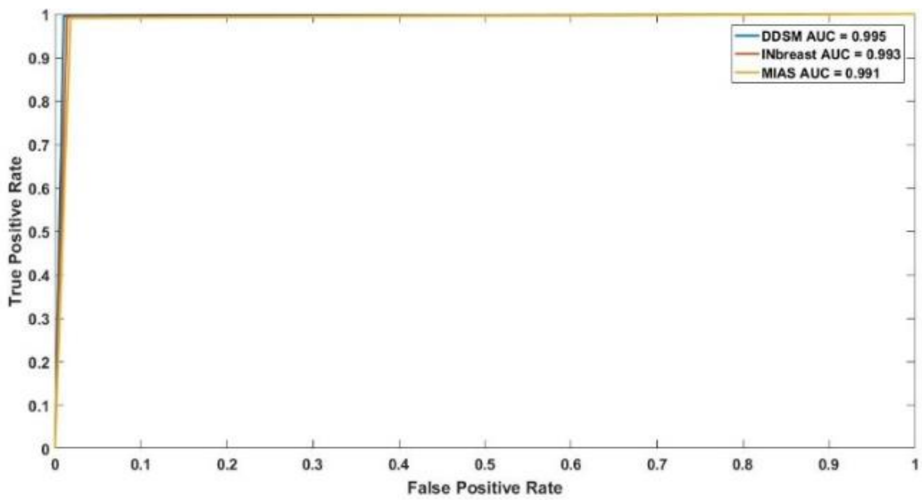

Figure 3. ROC analysis

The area under curve (AUC) concerning the TP rate and FP rate is generated in this analysis to demonstrate the breast cancer diagnosis model's superior performance. The proposed system implements a novel YOLO-based attention network segmentation technique that accurately segments the breast region for a successful illness prediction. The YOLO attention segmentation model greatly enhances the accuracy of the suggested model's classifier detection.

The performance of the proposed GADCN-LOA classifier and conventional deep learning is then validated and compared using the MIAS dataset, as shown in Figures 4 to 6 and the error rate is shown in Figure 7. Several metrics have been used in this inquiry to assess performance. The enhanced F1-score values, sensitivity, accuracy, and precision are frequently used to gauge the classifier's effectiveness. Overall, the findings demonstrate that the proposed GADCN-LOA in conjunction with a YOLO-attention network segmentation model produces superior performance results when compared to the other deep learning models.

The overall performance evaluation results of the suggested YOLO-based GADCN-LOA technique employing the DDSM, INBreast, and MIAS datasets are shown in Figures 8 and 9. To ascertain the accurate detection outcomes of the suggested classifier, performance parameters are created and examined for every benchmarking dataset that is accessible to the general public. For every breast image dataset taken into consideration in this work, the estimated findings demonstrate that the suggested GADCN-LOA in conjunction with a YOLO segmentation model functions brilliantly. Using the proper image normalization and segmentation techniques greatly enhances the detection outcomes in the proposed framework. Figure 10 validates and compares the precision of standard machine learning [32] and the proposed GADCN model using the WDBC dataset. Similar to this, the WDBC and WBCD datasets are used to compare the existing and proposed classification models, as shown in Figure 11. In this paper, classifier accuracy is confirmed and compared for this analysis.

Figures 12 to 16 validate and compare the accuracy of the existing [32], [33] and proposed algorithms by using the DDSM, MIAS, and INBreast datasets respectively. This comparison research reveals that the YOLO attention network segmentation integrated GADCN-LOA model yields better outcomes than the other models. Additionally, the proposed GADCN-LAO model is contrasted with some other contemporary breast cancer detection methodologies using the DDSM and MIAS datasets, as depicted in Figures 15 and 16, respectively. Since the activation function in the suggested classification model is calculated using the best possible LOA optimal value. As a result, the suggested framework significantly improves the classifier's training and testing outcomes, and the YOLO-based GADCN-LAO approach outperforms the previous models. Also, it supports obtaining an average accuracy of up to 99% for all the datasets. From the results, it is clear that the proposed methodology efficiently predicts breast cancer by employing novel techniques at different stages. Though it provides better results, the need of large dataset is required to perform the analysis. Further, advanced YOLO methods can be opted for training and processing with minimal time.

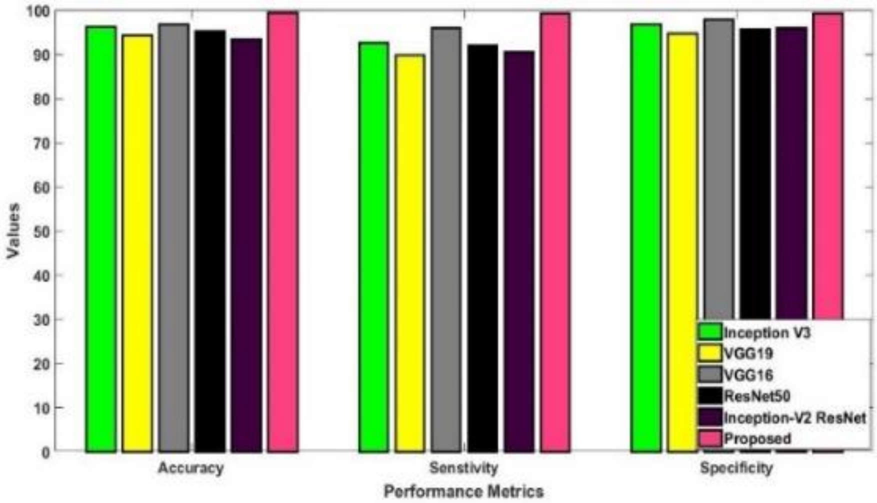

Figure 4. Performance evaluation using the MIAS dataset

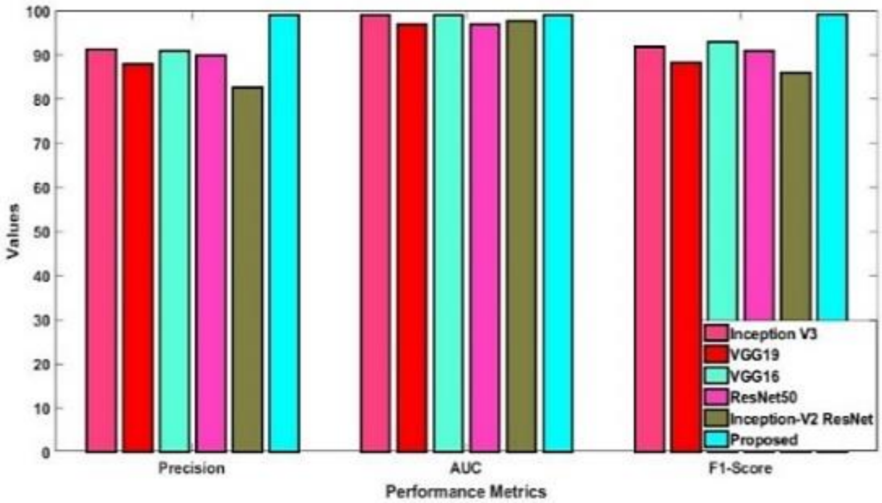

Figure 5. Precision, F1-score, and AUC analysis using the MIAS dataset

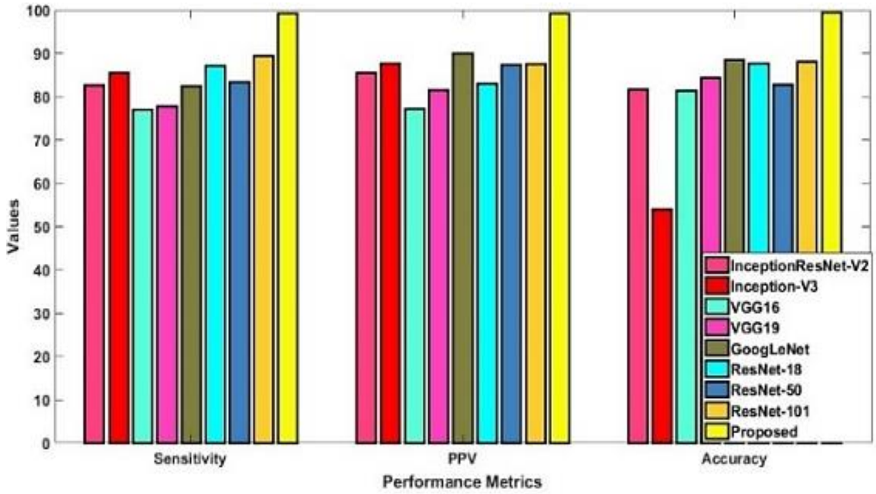

Figure 6. Comparative analysis between the deep learning architectures using the MIAS dataset

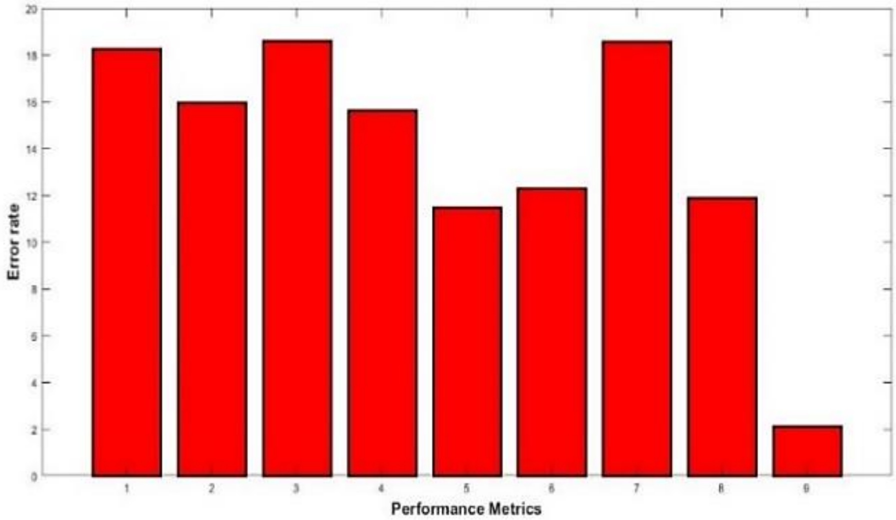

Figure 7. Error rate

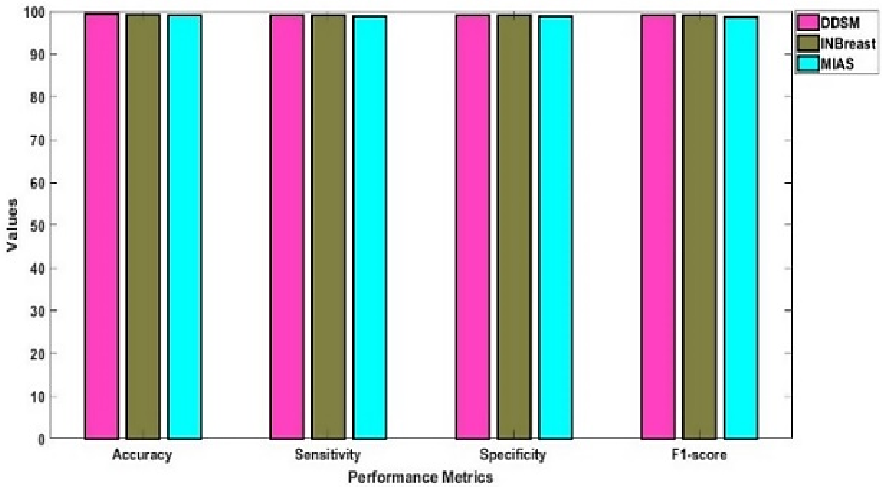

Figure 8. Performance analysis of the proposed YOLO-based GADCN-LOA model using different datasets

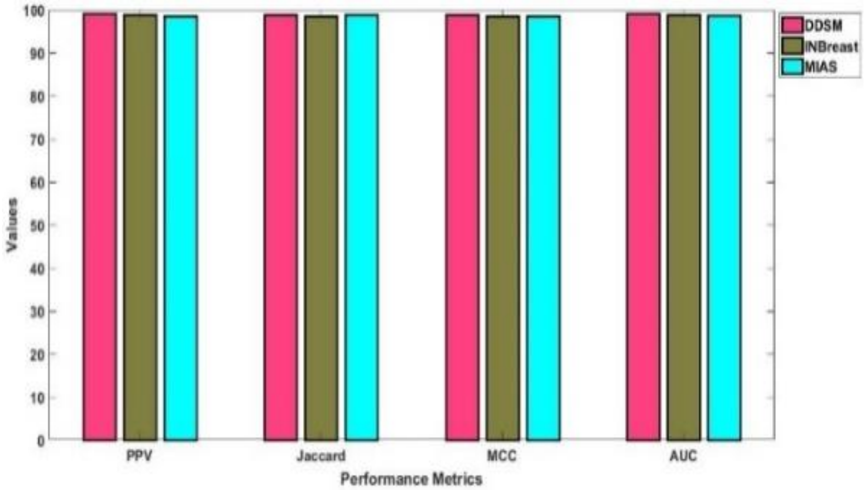

Figure 9. Detection performance analysis of the proposed YOLO-based GADCN-LOA model using different datasets

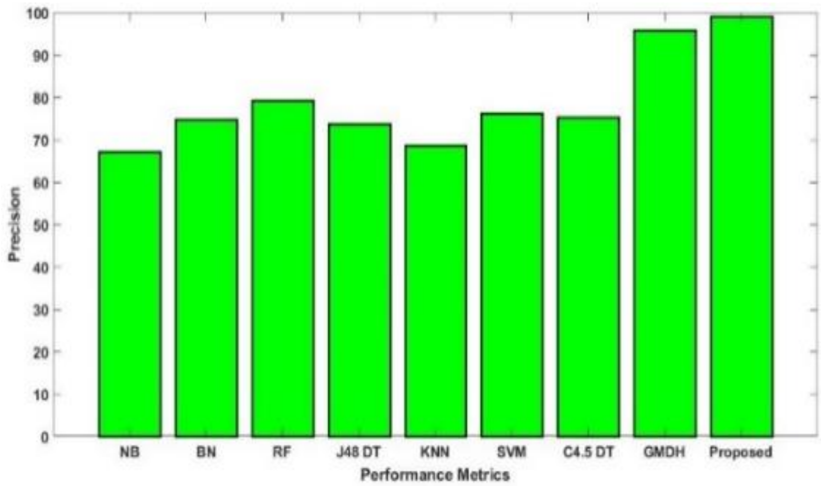

Figure 10. Precision analysis using the WDBC dataset

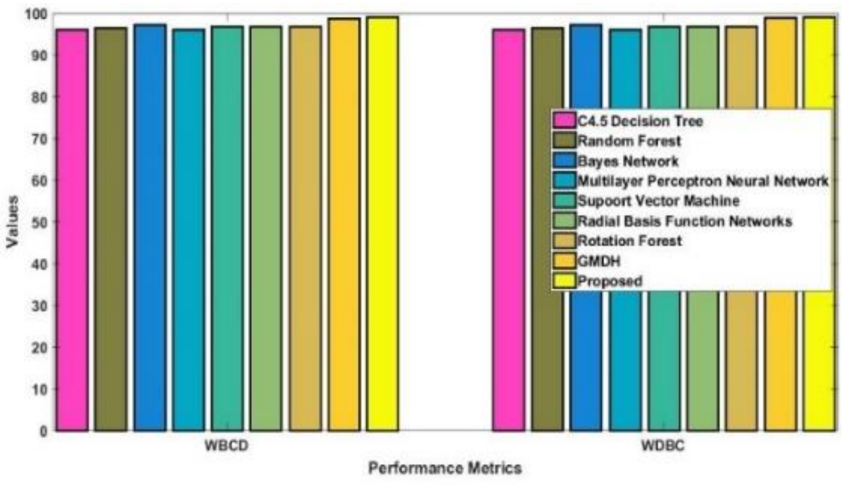

Figure 11. Comparative analysis using WBCD and WDBC datasets

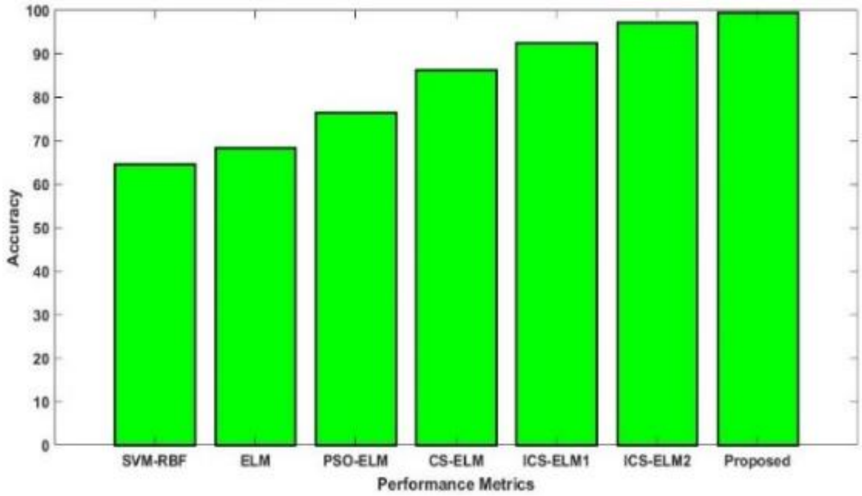

Figure 12. Accuracy using DDSM dataset

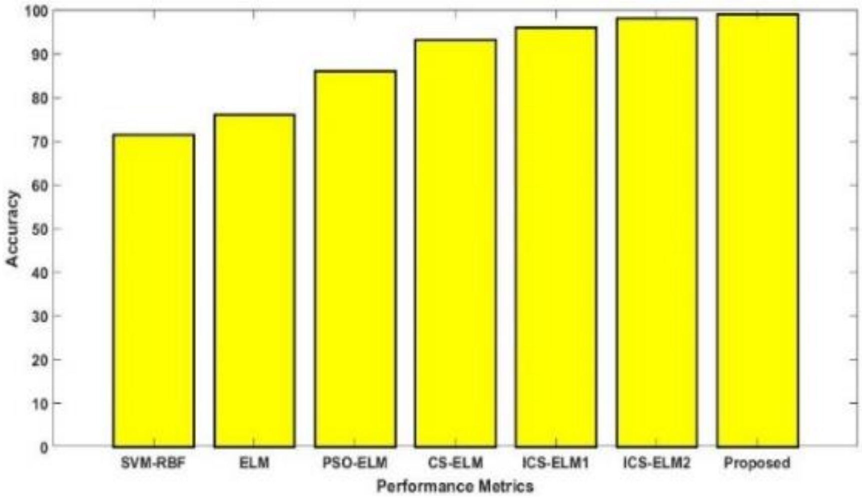

Figure 13. Accuracy using the MIAS dataset

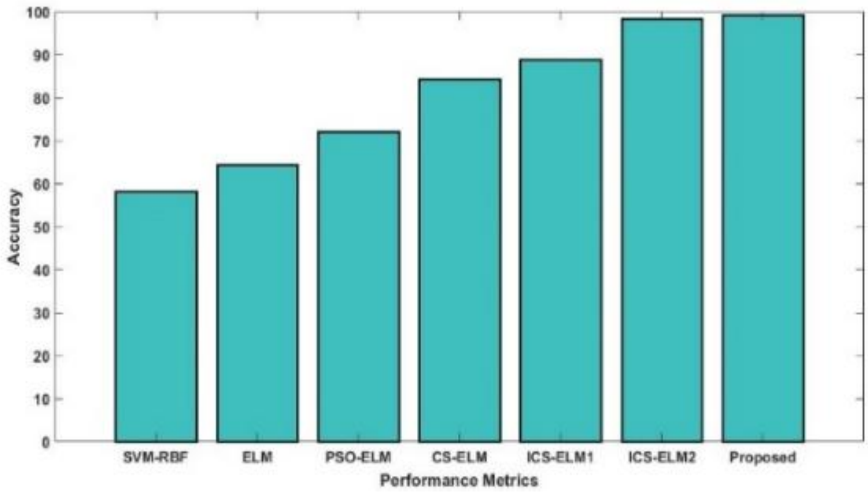

Figure 14. Accuracy analysis using INBreast dataset

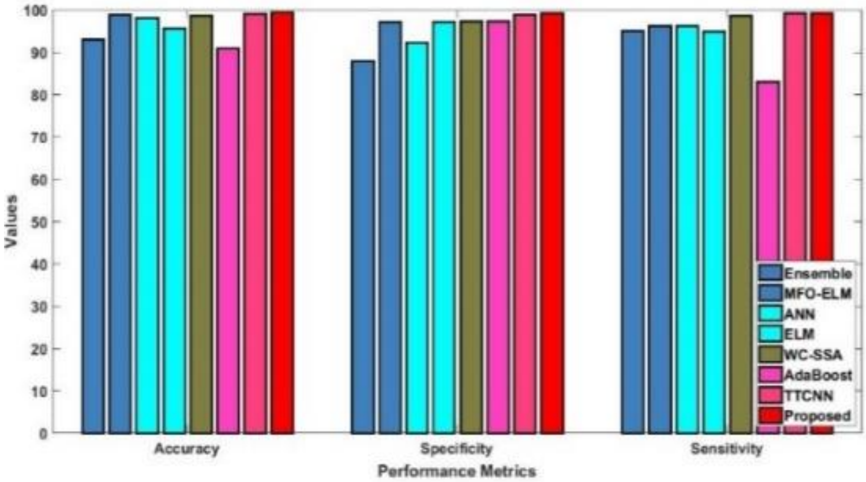

Figure 15. Comparative analysis using DDSM

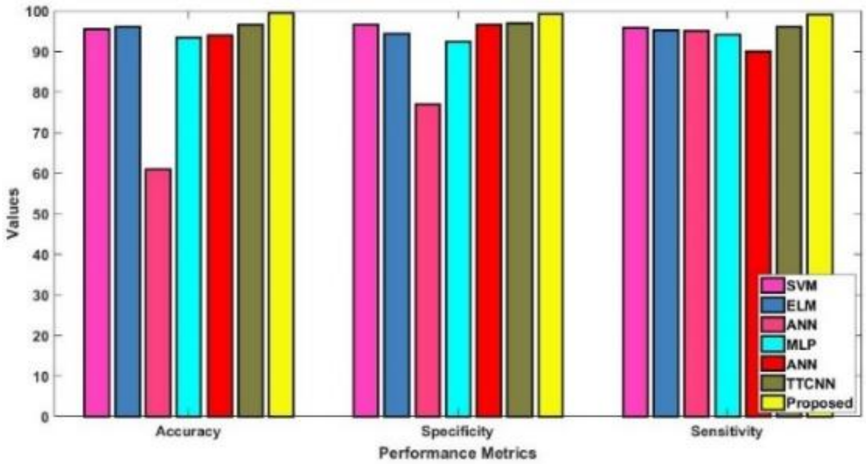

Figure 16. Comparative analysis using MIAS

4. CONCLUSION

This paper presents a novel and intelligent framework, named, YOLO-based GADCN-LOA for the recognition and categorization of breast cancer. In this framework, a group of advanced image processing techniques are implemented for precise breast cancer identification. The CLAHE model is used to perform initial preprocessing on the input mammograms received from the given set. This preprocessing includes image enhancement, histogram equalization, noise removal, and normalization operations. This form of preprocessing approach cuts down on training and testing time while assisting in reducing classification errors. Then, the breast region is more accurately segmented from the preprocessed image using a unique attention network model based on YOLO. It is a kind of lightweight deep-learning architecture that segments the breast region with low time consumption and reduced over-segmentation. Furthermore, the GADCN-based classification algorithm is utilized in this system to effectively forecast the healthy and cancer-affected images with high precision and detection accuracy. The optimal solution produced from the LOA is used to estimate the activation function during classification. By using the combination of CLAHE, YOLO attention network, GADCN, and LOA models, the overall breast cancer detection efficacy is greatly improved in the proposed system. Moreover, some of the popular breast image datasets are used in this study for system validation and comparison. The obtained results reveal that the proposed YOLO-based GADCN-LOA model provides effective performance results for all the datasets used in this study with an average accuracy of 99%. This work can be extended in the future by implementing a new CAD model for the detection of breast cancer and for other diseases.

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