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Original Article

Hybrid Transfer Learning of Mammogram Images for Screening of Micro-Calcifications

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Abstract - *Breast cancer is a deadly disease occurred in women due to modern lifestyles. It is a second serious disease to women's health, both physically and psychologically. Computer-aided design-based approaches support clinicians in the early diagnosis of breast cancers. It uses machine learning and deep learning algorithms to detect breast cancers in mammogram images accurately. This work proposes the hybrid ResNet and Bidirectional Long Short-Term Memories (BiLSTM) based transfer learning model for automatic micro calcifications classification in mammogram images. The hyperparameters of the proposed hybrid model are tuned by the Eurasian oystercatcher optimizer (EOO) to get superior performance in classification. The proposed model is applied in the MIAS database for classifying benign and malignant stages and compared against previously proposed models. The proposed model achieved a better result in all iterations for accuracy, precision, recall, and specificity 98.4%, 98.2%, 98.4 % and 99.4 %, respectively.*

Keywords - *Breast cancer, Hybrid model, EOO and BiLSTM.*

1. Introduction

Breast cancer is the most common severe disease of females in developing countries. The early diagnosis and treatment of breast cancer can reduce the death rate by about 30% over the previous years. Recently, mammography has received great attention for the detection of breast cancer. Mammography uses x-ray -technology to clearly show the patterns of cancers more than other methods such as Computed Tomography (CT), Ultrasonic and Magnetic Resonance Imaging (MRI). The important sign of breast cancer is the appearance of small and bright white spots in mammography images. Mammograms allow us to analyze these spots from different angles for an accurate cancer diagnosis. By using morphological distributions, shapes and their counts, it can be classified into either macro calcifications or microcalcifications. Macro calcifications don't belong to breast cancer. Microcalcifications are combined to form clusters of calcifications occurred due to changes in normal breast activities and the early stages of breast cancers. The accurate processing and identifications of microcalcifications edges are needed for the early diagnosis of breast cancers.

Machine Learning (ML) algorithms have been extensively used in medical image processing, such as segmentation, classification, object findings, etc. Subsequently, Deep learning (DL) is a subcategory of ML, which consist of multiple interconnected layers to solve the issues of learning from multiple representations. Convolutional Neural Networks (CNNs) are the well-known learning model for medical image segmentation and classification problems.

Many of the DL-based architectures proposed for the classification of breast cancers are CNN based. In image processing, CNN can process spatial data but is unsuitable for sequential correlations. Conversely, Recurrent Neural Networks (RNNs) are best suitable for sequential correlations but cannot process the features in parallel. It also suffered from vanishing gradients and overfitting problems. Long short-term memory (LSTM) is a type of RNN that is introduced to solve the problems in RNN with effective sequential data handling.

This work proposed a hybrid DL model which combines both CNN and LSTM models with transfer learning. It considers temporal features of the image for accurate classifications. The contributions of the proposed work are as follows:

- Performing ESPNet-based segmentation to get strong features
- To develop a TL-based hybrid classification model for the early detection of micro-calcifications.
- The proposed approach is compared against other models.

This work is structured as follows. Section 2 explains the existing works. The architecture of the proposed hybrid model is presented in Sect. 3. Section 4 illustrates the experimental results on MIAS datasets. Finally, the conclusion is described in Sect. 5.

2. Related work

There are different works in the literature proposing different methods for the detection and classification of microcalcification. Chatterjee et al. 2011 proposed a simple thresholding method for Micro-calcification Detection. It includes median filter-based preprocessing and uses 5 × 5 unsharp masking to enhance the edges of the structures in an image. For segmentation, multivalued thresholding is used.

The breast cancer detection process can be improved by properly handling the noises in mammogram images. Bria, A et al. 2018, analyzes the impact of intensity-dependent quantum noise in mammograms. Also, an adaptive variance stabilizing transform was derived for balancing that noise and improving the quality of the image. Zhu, L et al. 2019 proposed a successive mean quantization transform (SMQT) algorithm for Micro-calcification Detection in Mammograms. The proposed approach includes three stages: combined top-hat transform and SMQT-based preprocessing, obtaining calcification area by wavelet transforms and pulse-coupled neural network-based detection. Results show that the proposed method can achieve the accuracy of 96.32% in 84 mammograms from the MIAS database

The new type of deep learning model, EfficientNet, is proposed by Tatsuaki Kobayashi et al. 2022. Adding more layers, the conventional model can be converted to the EfficientNet model. Results show that the proposed EfficientNet model outperforms other models by achieving an accuracy of 94% on different breast cancer data sets.

Pati, D. P analyzed the performance of different filters in mammogram images and proposed a new hybrid median filter to enhance the quality of the image. The performance of filters is compared in terms of Signal to Noise Ratio (SNR), Peak Signal to Noise Ratio (PSNR) and structural similarity (SSIM).

Loizidou, K et al. 2019 proposed a new method for breast cancer detection using digital temporal subtraction of mammogram pairs. Initially, temporal subtraction of images is carried out with demon-based registration. Then, the subtracted images are processed for classification using a support vector machine. The accuracies achieved are 92.63 % for benign classification and 94.62 % for malignant stage classification. Methods based on deep learning models, which unify the automatic feature extraction and detection, have newly been used to examine breast cancers in a mammogram image. Songsaeng, C et al. 2021 propose the DL-based multi-scale attention network. The proposed model has unique advantages of hierarchical block-wise and layer-wise feature representation to achieve a higher classification accuracy.

Saubhagya, V. K et al. 2016 proposed a neural network (NN) based segmentation for microcalcification detection. It uses the Levenberg-Marquardt algorithm (LMA) algorithm to find a minimum of a function over a space of parameters for segmentation**.** The proposed NN model achieved the highest segmentation accuracy of 91.64%, exceeding the existing method accuracy by 2.8%. The ML algorithm of Ensemble of Decision Trees (EDT) is used by Loizidou, K et al. 2020 for detecting and classifying breast cancer. The proposed ensemble model combines Naive Bayes, Random Forest and support vector machines to classify cancer severity levels**.** As a result, the accuracy of ensemble classifiers is higher when they are used individually for classification.

Sathyan, A et al. developed a U-Net deep learning model for breast cancer segmentation. U-net is a fully convolutional neural network segmenting images without any hidden layers. The proposed model can find most mass regions with the highest dice score and sensitivity rate. Rehman, A. U et al. 2015 proposed a diverse feature-based Micro-calcification Detection in Mammograms. It uses phylogenetic trees and local binary patterns to generate a diverse feature for further classification. The Support Vector Machine with RBF kernel is used for classification.

Renbin Peng et al. 2009 proposed a stochastic resonance (SR) noise-based filtering approach for noisy mammograms. It effectively handles the mismatch due to the Gaussian assumption. Other preprocessing techniques greatly improve the SNR rate of the image.

The hybrid DL model proposed by Agrawal, S et al. 2018 combine a neural network with a linear classifier. The DL model of VGG16 is used for feature extraction and classified using a linear classifier. The linear Classifier achieves 9.2 % of false negatives and 9.54 % of false negatives, which shows that a higher ratio of the outputs classified is correct, thus proving the greatest performance. Ghamdi, M. A et al. 2020 proposed a dense connectivity-based modified U-Net model called DU-UNet for classifying Arterial Calcifications in a Mammogram. In DU-UNet, the dense module is used to learn the features deeply, and a concatenation block is added to merge dense module outputs. Results show that the model with dense blocks increases the accuracy of the individual models in Arterial Calcifications detection.

3. Proposed hybrid model for Micro-calcification classification

The block diagram of the proposed work is shown in Figure 1. It consists of four steps: preprocessing, segmentation using ESPNet, optimized hybrid model classification and performance analysis. These blocks are explained in the following subsections.

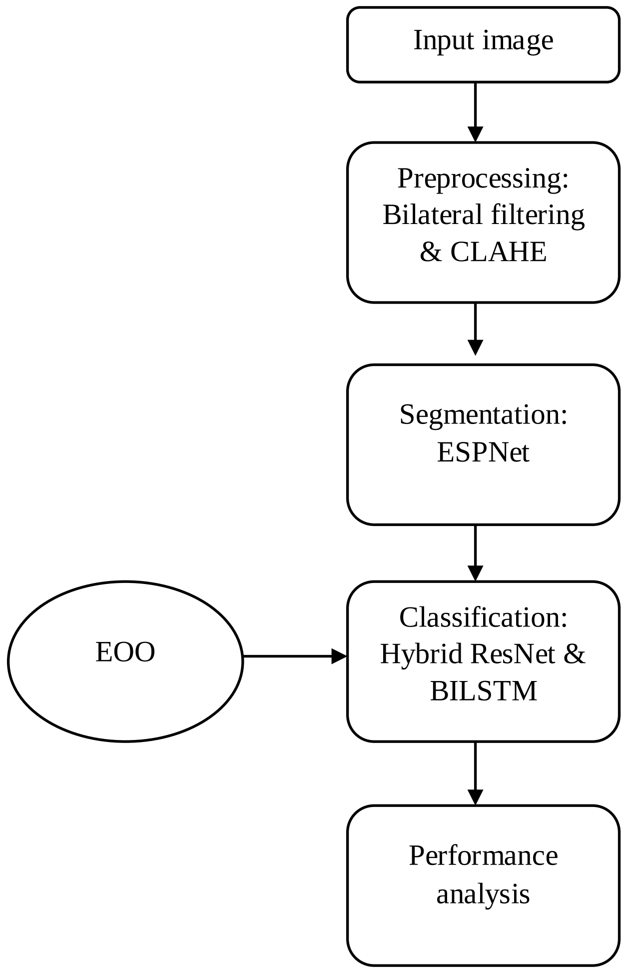

Fig. 1 Block diagram of the proposed classification model

3.1. Preprocessing

In preprocessing stage, the bilateral filter reduces the halo effect. The bilateral filter has better noise reduction capability and is more advanced than a median filter. Then, the contrast-limited adaptive histogram equalization (CLAHE) technique is applied for contrast enhancement. CLAHE divides the entire image into tiles and calculates a histogram for each region to avoid noise enhancement and reduce a shadowing effect. Here, the normal, benign, and malignant images are enhanced using the bilateral filter and CLAHE.

3.2. ESPNet

This work segmentation is carried out by using ESPNet. In ESPNet, the traditional convolutional operation is decomposed into point-wise convolutions and a spatial pyramid of dilated convolutions [20]. The concept of point-wise convolutions supports the ESPNet to reduce processing time. The spatial pyramid of dilated convolutions is used to resample the feature maps to absorb the representations from a large receptive field. The ESP module includes point-wise convolution (PWC) and dilated convolutions (DC). The PWC performs 1*1 convolution to highlight a high-dimensional feature map, and the DC block performs resampling of the features with a dilation rate of 2k−1, k = {1,⋯, K}. This decomposition effectively reduces memory requirements and several parameters.

The number of parameters in the ESP module is $(\frac{N1N2}{H}+\frac{nN2^2}{H})$ with the effective receptive field of $[(n-1)2^{H-1}+1]^2$. Where N1 and N2 denote the number of input and output feature channels, and H is the hyperparameter. The number of parameter requirements is reduced by a factor of $\frac{n^2N1H}{N1+n^2N2}$ in ESPNet from n^2N1N2 in the conventional model. The effective receptive field is increased by the factor of $[2^{H-1}]^2$

3.3. Proposed TL-based hybrid model

TL is the reusing of a pre-trained model or transferring the knowledge to enhance the performance of the CNN model. The trained features and model parameters are reused to increase the classification performance of the learning model. Compared to other models, the ResNet-18 has been identified as the best suitable model for medical image classification due to its shallow architecture and less training time. ResNet-18 architecture consists of a 7*7 convolutional layer, 2 pool layers, 5 residual blocks, and 1- fully connected (FC) layer. The architecture of ResNet-18 is shown in Figure 2. The convolution layer operations can be avoided by using skip connections. RB1 is a conventional ResNet block, and RB2 is a ResNet block with 1 * 1 convolution. In the proposed hybrid ResNet-BiLSTM model, the final FC layer is replaced with flattened and BILSTM layers to consider a temporal feature of the image. Adding a flattened layer converts the data into a one-dimensional array and prepares the input for LSTM layers. The LSTM model is introduced to process the sequential data and to overcome the drawback of the vanishing gradient and overfitting problem of RNN. The regular LSTM model process the data in a single direction, but in BILSTM, the data is processed in both forward and reverse directions. The proposed model includes BILSTM layers and is convolutional to improve the classification performance. The extracted temporal features from LSTM layers are given as input to the FC layer, and final classification is done using SoftMax

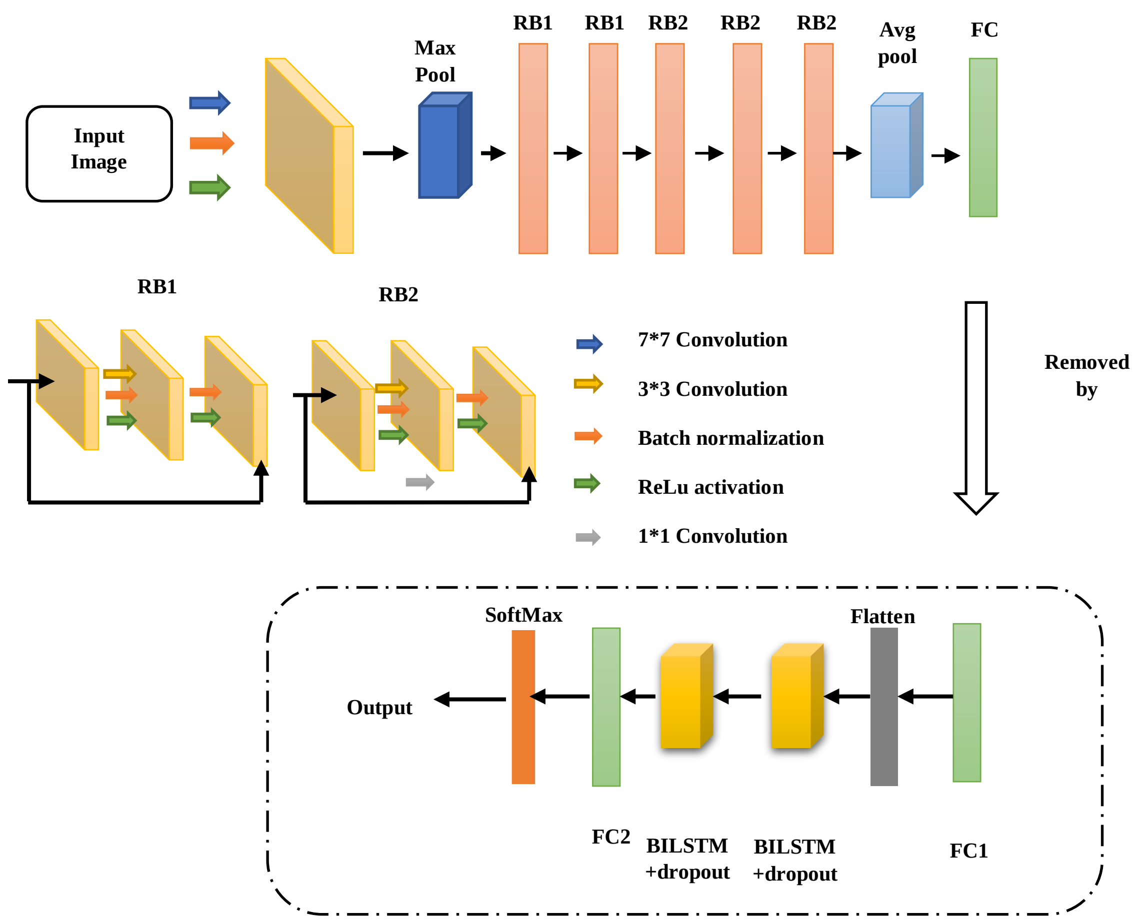

Fig. 2 Proposed ResNet & BiLSTM hybrid model

3.4. Hyperparameters tuning using EOO

Many real-world problems can be solved by using optimization algorithms. The search space for a problem is increased gradually based on its size. Conventional optimization algorithms can not solve these problems. Metaheuristic algorithms have been introduced to handle this problem and identify the best solution in a larger search space. Eurasian oystercatcher optimizer (EOO) is a recently proposed optimization algorithm inspired by the food searching behaviour of oystercatcher. The searching behaviour for the best mussels is mathematically modelled to find the best solution for the problem.

In the oystercatcher lifestyle, the birds' energy depends on the mussels' size. The mussels with larger sizes and shells take more time to open and sometimes cannot be opened even if it has more calories. The mussels with a size between 30 and 45 mm can be easily opened and are mostly preferred by oystercatcher to eat. The size of mussels is directly related to calories gained, energy consumed and time spent for opening by the oystercatcher. Here, finding suitable mussels with the optimum size is formulated as an optimization problem. The position of candidate mussel (P_i) and the final energy (TE) of the oystercatcher can be formulated as follows:

$$TE = t + E + l * rand * (P_{best} - P_{i-1}) \quad (1)$$

$$P_i = -P_{i-1} * Ca \quad (2)$$

Where l is the mussel length that varies from three to five, r and is the random number that varies between zero to one, and i is the iteration.

t is the time required to open the shell, and it can calculate as follows:

$$t = ((\frac{l-3}{5-3}) * 10) - 5 \quad (3)$$

ca is calorie values gained by the corresponding mussel, and it can be computed as follows:

$$Ca = ((\frac{l-3}{5-3}) * 2) + 0.6 \quad (4)$$

E is present energy, and it can be calculated as follows:

$$E = ((\frac{i-1}{n-1}) - 0.5), where\ i > 1 \quad (5)$$

The hyperparameters of the learning model are categorized into two types: structure-based and learning based. The learning-based parameters include Momentum, epoch number, batch size and learning rate. The calculated fitness by EOO is used to update the hyperparameters. For every iteration, the model is constructed using new hyperparameters and ready to achieve the highest classification accuracy. The steps involved in EOO-based parameter tuning are given below:

Steps in hyperparameter tuning
S1. Read the current hyperparameter value as the input data.
S2. Initialize the EOO algorithm containing the E, X, and Ca.
S3. Set initial population representing model hyperparameters.
S4. Use the initial population to train the hybrid model.
S5. Estimate the MSE of various populations as the corresponding fitness value.
S6. If the fitness meets the required classification accuracy, go to step 8, else continue
S7. Increase the number of iterations and then go to Step 4.
S8. Return best hyperparameters.

4. Experimental results

The performance evaluation of the hybrid classification model is carried out using the MIAS database. The data set consists of 9,109 images collected from 92 patients with different magnifying factors. It comprises 2338 benign and 6771 malignant samples in PNG format. The sample data set image is shown in Figure 3. From the total, 70% of the data is used to train the model, and the remaining 30% is used to test the model. The proposed model is compared to other models in terms of Accuracy, Specificity, Recall and Precision rate measurements. These measurements can be defined as:

Accuracy = (TP + TN) / (TP + TN+FP +FN) (6)

Specificity = (TN) / (TN + FP) (7)

Recall = (TP) / (TP + FN’) (8)

Precision = TP / (TP + FP) (9)

Where FP is the false positive, FN is the false negative; TP is the true positive, and TN is the true negative of the samples.

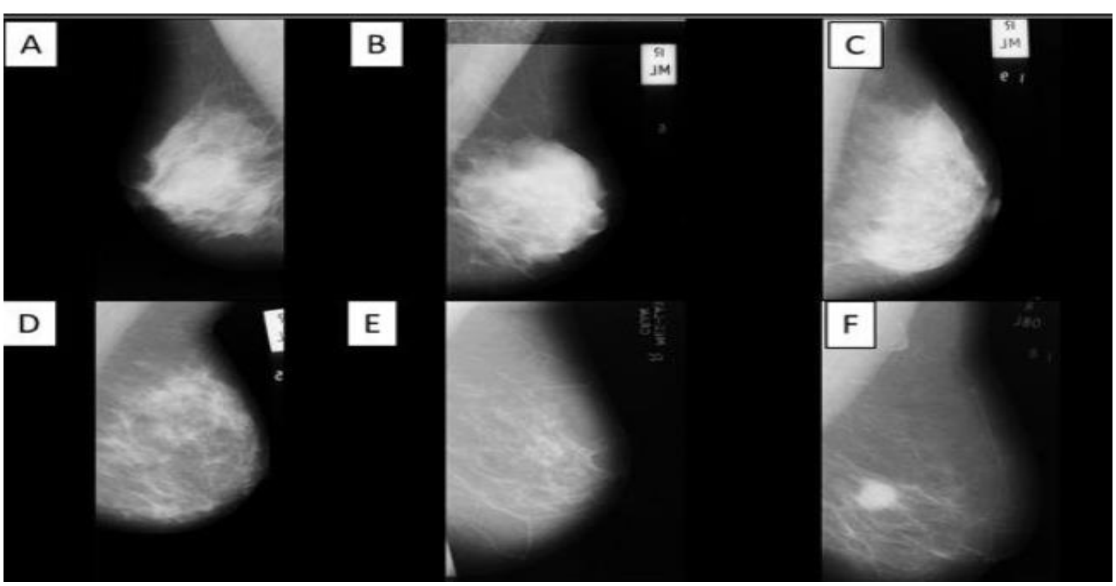

Fig. 3 MIAS data set images

Table 1. Classification performance of proposed and existing models.

Method	Accuracy	Precision	Recall	Specificity
[17]	90.70	90.2	90.41	97.2
[18]	92.78	92.6	92.3	98.4
[19]	93.34	93.42	92.54	97.83
Proposed	98.4	98.2	98.4	99.4

Table 1 shows the results after applying 15 iterations of learning and optimization. The proposed model achieved a better result in all iterations for accuracy, precision, recall, and specificity 98.4%, 98.2%, 98.4 % and 99.4 %, respectively. The model proposed by the author [17] attained a result in all iterations for accuracy, precision, recall, and specificity are 90.70%, 90.2%, 90.4 % and 97.2 %, respectively. The model proposed by the author [18] attained a result in all iterations for accuracy, precision, recall, and specificity are 92.78%, 92.6%, 92.3 % and 98.4 %, respectively. The model proposed by the author [18] attained a result in all iterations for accuracy, precision, recall, and specificity are 93.34%, 93.42%, 92.54 % and 97.83 %, respectively. Compared to all the models, the prosed model shows superior performance in all the performance parameters. The performance of the proposed model is graphically shown in Figure 3.

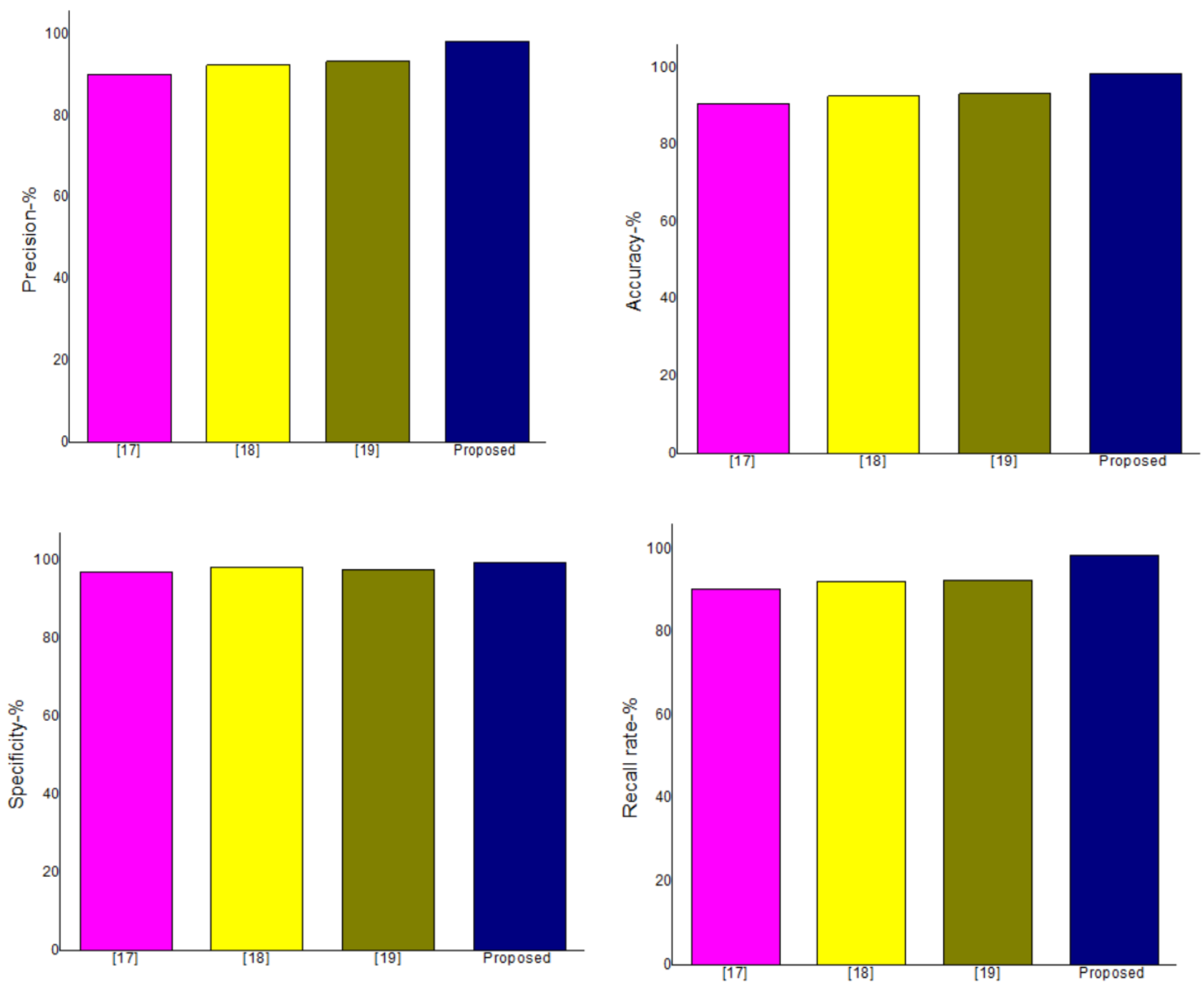

Fig. 3 Performance analysis of accuracy, specificity, recall and precision rates.

5. Conclusion

Mammography is a promising diagnosing approach for the detection of breast cancer. But the early detection and classification are difficult for clinicians due to the small size of microcalcification clusters. This work proposed a hybrid TL model for the automatic micro calcifications classification of breast cancer images. The performance of the TL model is enhanced with metaheuristic optimization. Results show that the proposed model outperforms in terms of accuracy, specificity, sensitivity and precision rates of previously proposed models. The proposed model achieved a better result in all iterations for accuracy, precision, recall, and specificity 98.4%, 98.2%, 98.4 % and 99.4 %, respectively.

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