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Combining the advantages of radiomic features based feature extraction and hyper parameters tuned RERNN using LOA for breast cancer classification

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ABSTRACT

This paper proposes Combining the Advantages of Radiomic features based Feature Extraction and Hyper Parameters tuned Recalling Enhanced Recurrent Neural Network (RERNN) using Lizard optimization Algorithm (LOA) for Breast cancer Classification. Here, breast cancer images are taken from the real time dataset collected from VPS hospital and then the images are preprocessed using Altered Phase Preserving Dynamic Range Compression (APPDRC) to remove the noises. Then the radiomic features, such as morphologic features, gray-scale statistic features and Haralick texture features have been extracted utilizing Entropy Based Local Binary Pattern (ELBP). These extracted features have presented to Recalling Enhanced Recurrent Neural Network (RERNN) classifier. Hence, Lizard optimization Algorithm (LOA) is utilized to optimize the Recalling Enhanced Recurrent Neural Network (RERNN). The proposed approach is executed in MATLAB platform, then the performance is compared with different existing approaches. This approach is applicable in real time applications for screening the abnormalities of the breast cancer at initial stage, thus, determining the proper treatment to be given to the patient for decreasing deaths caused by breast cancer. The novelty or aim of this paper is to diagnose the breast cancer in early stage by extracting the radiomic features and to classify the types (Malignant, Benign, normal) of breast cancer with high accuracy by reducing the computational time and error rate. The simulation outcomes demonstrate that the proposed FE-APPDRC-ELBP-RERNN-LOA attains the accuracy of45.75%, 37.64%, 24.64 %is higher than the existing methods.

1. Introduction

Nowadays, breast cancer becomes one of the dangerous diseases that are affecting all over the world [1]. This disease mostly affects women and affects even men also and it is cured while detecting the diseases in early stage. In this the death rate also increases due to the cancer diseases [2]. As a result, detection of breast abnormalities in its early stage can degrade the death rate [3]. "The mammography is an efficient screening technique for breast cancer detection. This technique is widely used due to its less expensive nature and it increases the sensitivity of lesion areas, the prediction and classification accuracy can be affected by many factors, such as breast density, structural complex, the presence of low contrast tissues" [4,5]. The mammogram breast cancer images are taken from the real time dataset. Then the images are preprocessed to remove the noises [6,7]. Breast cancer starts to grow from normal tissues and divided to a large number of cell in the form of roots. In this the cancer cell consists of many more cells and the roots that are spread to the blood and the other parts more easily [8,9]. So, in the later stage the disease may not be cured easily [10,11]. While large amounts of the patients are increasing day-by day the doctors work load also increasing to detect the cancer [12,13]. So many deep learning algorithms and the feature extracting methods are increased to detect the cancer [14]. In this work, does not provide sufficient accuracy and the error rate is increased by increasing computational time, so radiomic feature extraction method is proposed [15]. The radiomic features are extracted from the input imagery [16]. Radiomic is defined as the extraction as well as examination of a great quantity of quantitative image features from medical imageries that is widely discussed in many existing papers

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and the predict analytical or extrapolative associations among quantitative image features and medical outcome (9, 10) [17]. There several methods like Gray Level Co-occurrence Matrix (GLCM) [18], k-Nearest Neighbor (k-NN) [19] classifier are used to extract the radiomic features but that methods do not provides the sufficient outcome.

- **Problem statement**

The complex environment of feature extraction process in classical deep learning approaches degrades the performance of the system regarding efficiency with accuracy [20–22]. The previous technique, namely Random Forest, kNN (k-Nearest-Neighbor) and Naïve Bayes, [22] does not provide sufficient accuracy and the error rate is increased [23–28].

- **Application and novelty**

This method is used to clarify the misclassification errors during the classification process, while screening the breast cancer mammogram images. This method is applicable in real time applications for screening the abnormalities of the breast cancer in starting stage, thus, determining the proper treatment to be given to the patient for decreasing deaths caused by breast cancer. The novelty or aim of this paper is to diagnose the breast cancer in early stage by extracting the radiomic features and to classify the types (Malignant, Benign, normal) of breast cancer with high accuracy by reducing the computational time and error rate.

In this paper, breast cancer images are taken from the real time dataset collected from VPS hospital and then the images are preprocessed using APPDRC [28]. Then the radiomic features such as morphologic features, grayscale statistic features and Haralick texture features are extracted using the Entropy Based Local Binary Pattern (ELBP) [29–33]. These extracted features are given to RERNN [34] classifier. Therefore Lizard Optimization (LOA) [35] is utilized to optimize the Recalling enhanced Recurrent Neural Network.

The main contribution is summarized below;

- In this paper, combining the Advantages of Radiomic features based Feature Extraction and Hyper Parameters tuned Recalling enhanced Recurrent Neural Network (RERNN) using Lizard Optimization (LOA) is proposed for diagnosis of Breast Cancer in its early stage.
- Initially, the Breast cancer mammogram images are taken from the real time dataset collected from VPS hospital.
- Secondly, the mammogram breast cancer images are pre-processed using Altered Phase Preserving Dynamic Range Compression filtering scheme, which preserves the local features suitable for better boundary detection and to improve the quality of the image.
- Thirdly, the radiomic features such as morphologic features, grayscale statistic features and Haralick texture features have been extracted by Entropy Based Local Binary Pattern.
- Here entropy has the following significance for extracting the features such as; Entropy of the local absolute dissimilarity is employed to create the corresponding robust against local spatial structural changes.
- Then the extracted radiomic features are classified using the Recalling enhanced Recurrent Neural Network (RERNN) classifier
- At last the weight parameters of the Recalling enhanced Recurrent Neural Network (RERNN) is optimized using the Lizard optimization Algorithm (LOA) performs the classification of breast cancer images into benign, malignant and normal.
- The Experimental evaluation is done by MATLAB platform. The efficiency of the proposed FE-APPDRC-ELBP-RERNN-LOA based classification framework is estimated with the help of several performances evaluating metrics like sensitivity, precision, recall, f-measure, specificity, accuracy, error rate and various radiomic features such as mean, variance, Standard deviation, Kurtosis, Skewness, Entropy.
- The real time breast cancer images considered for evaluation is taken from real time database from VPS Lakeshore hospital. The experimental results obtained from the proposed classification framework shows that it obtains better classification accuracy with less error rate and computational complexity than the compared existing classification approaches, such as automatic breast cancer detection in digital mammograms using moth flame optimization (MFOA) on the basis of extreme learning machine (ELM) technique (FE-LWT-MFO-ELM)[36], automatic detection of breast cancer using hybrid extreme learning machine by means of Fruit fly Optimization Algorithm (ELM-FOA) classifier (FE-GLCM-FOA-ELM)[37], recognition of breast cancer with fusion of Cranio caudal (CC) and Medio lateral Oblique (MLO) view using hybrid method depending on binary firefly algorithm with optimum-path forest classifier (FE-LBP-Hybrid-FOA-OPFC)[38], automated mammogram breast cancer detection utilizing optimum consolidation of convolutional and recurrent neural network (FE-GLCM-Hybrid CNNRNN-FC-CSO)[41], Improved breast cancer classification through combining graph convolutional network and convolutional neural network (FE- BDR-CNN-GCN) [43], detection and classification of breast cancer from digital mammograms using hybrid extreme learning machine classifier (FE-GSO-Hybrid ELM-FOA) [44] respectively.

Remaining paper is structured as. Section 2 delineates the literature survey. Section 3 describes about the Proposed method for detection with classification of breast cancer utilizing Entropy Based Local Binary Pattern (ELBP) based Radiomic features based Feature Extraction Recalling Enhanced Recurrent Neural Network (RERNN) hyper parameter tuned using Lizard optimization Algorithm (LOA) Approach. Section 4 demonstrates the result and discussion. Section 5 concludes the paper.

2. Literature survey

Muduli, et al. [36] have presented a automatic breast cancer detection in digital mammograms using MFOA on the basis of extreme learning machine (ELM) technique. Here, the input breast cancer images were taken from the MIAS dataset, then the images were preprocessed to remove the noises. Then the features were extracted using the lifting wavelet transform (LWT). The images were classified by using extreme learning machine (ELM) classifier. The ELM parameters were optimized using the moth flame optimization (MFO) algorithm. The breast cancers were classified on the basis of normal or abnormal and benign or malignant with the accuracy of 94.76% (normal Vs abnormal), 97.80% (benign Vs malignant). This method has the limitation of less number of features are extracted.

Melekoodappattu et al. [37] have presented a automatic detection of breast cancer using hybrid extreme learning machine by means of Fruit fly Optimization Algorithm (ELM-FOA) classifier. Here, mammogram breast cancer images were taken for breast cancer detection. Then the images were preprocessed to remove the noises, then the features were extracted using Gray Level Co-occurrence Matrix (GLCM) method. Then the extracted features were selected to classify the images depending on normal, benign and malignant. The images were classified using the extreme learning machines (ELM) classifier. Extreme learning machines (ELM) weight parameters were optimized using the Fruit fly Optimization Algorithm (FOA). The experimental performance shows the accuracy of 97.5%. The limitation of this method was error rate increased due to the large number of features are extracted.

Sasikala et al. [38] have presented a recognition of breast cancer with fusion of Cranio caudal (CC) and Medio lateral Oblique (MLO) view using hybrid method dependingupon binary firefly approach with optimum-path forest classifier (Hybrid BFOA-OPFC). Here, the input breast cancer images were taken from the GLOBOCAN dataset, then the

images were preprocessed to remove the noises. The image features were extracted utilizing Local Binary Pattern (LBP), then the extracted features were Mediolateral Oblique (MLO) including Craniocaudal (CC) view mammograms. These features were fused using the hybrid method depending on binary firefly algorithm with optimum-path forest classifier (Hybrid BFOA-OPFC). The presented method provides accuracy of 98.56%. The limitation was error rate increased due to feature fusion process.

Begum et al. [39] have presented a Combining optimal wavelet statistical texture and recurrent neural network (RNN) for tumor detection and classification. Here, input mammogram breast cancer images were taken from the MIAS dataset. The images were preprocessed to remove the noises. Then extracted the textural features, also the extracted features were classified utilizing recurrent neural network (RNN) classifier. There current neural network (RNN) parameters were optimized using the oppositional gravitational search algorithm (OGSA). The classified abnormal images were segmented and then separate the region of interest (ROI) region depends on modified region growing algorithm (MRG). This method shows 96.43% accuracy. The presented method has the limitation of classification error.

Khandezamin et al. [40] have presented a detection with breast cancer classification utilizing logistic regression feature selection along Group Method Data Handling (GMDH) neural network classifier. Here, the breast cancer images were taken from 3 datasets: WBCD, WDBC, WPBC. The images were preprocessed to remove the noises. The features were extracted, and then the features were selected by logistic regression feature selection process. Then the images were classified using GMDH neural network was utilized to analysis of benign as well as malignant samples. The experimental results show the accuracy of 3 dataset as 99.4% for WBCD, 99.6% for WDBC, 96.9% for WPBC dataset.

Vo et al. [12] have presented a Classification of breast cancer histology images utilizing incremental boosting convolution networks. Here, the breast cancer diseases were detected using the histopathology images. The images were pre-processed to remove the noises. Then the features were extracted and classified using deep learning models with convolutional layers. The presented method was used to classify the images on the basis of breast biopsy images into 2 major clusters (carcinomas, non-carcinomas), 4 module (normal tissues, benign lesions, in situ carcinomas, invasive carcinomas). The presented method provides the accuracy of 96.45%. The limitation was high computational complexity.

Patil et al. [41] have presented the automated mammogram breast cancer identification utilizing optimum consolidation of convolutional and recurrent neural network. A median filter averts the input mammogram noise. Also, the optimized region growing segmentation was made for separating the tumor from the image, then the optimized region growing with the help of hybrid meta-heuristic approach named firefly updated chicken based CSO (FC-CSO). Then, feature extraction was carried out that aims to extract the features, via grey level co-occurrence matrix, gray level run-length matrix. The 2 deep learning approaches were: convolutional neural network, recurrent neural network. The grey level co-occurrence matrix and gray level run-length matrix were deemed as input to recurrent neural network, also the tumor segmented binary image was deemed as input to convolutional neural network. The outcomes display that the AND operation of 2 classifier output provides entire diagnostic accuracy.

Liu et al. [42] have presented a hybrid deep learning approach to predict Molecular Subtypes of Human Breast Cancer utilizing Multimodal Data. First, integrate the patient's gene along image modality data for structuring a multiple modal fusion structure. As per the various states, the feature extraction networks was set, then fuse the output of 2 feature networks depending on the designing of weighted linear aggregation. At last, the fused features were utilized to forecast breast cancer subtypes. In general, to lessen the dimensionality of higher dimensional data of gene modality as well as filter the data of image modality, the principal component analysis was employed. Moreover, the traditional feature extraction network was enhanced to attain the good performance. The outcomes display that the presented method gets more accurate with proficient for predicting breast cancer subtypes likened with deep learning model, Hybrid deep learning model. The presented method achieves 88.07% prediction accuracy in 10 times of 10-fold cross-validation.

Zhang et al. [43] have presented an improved breast cancer classification through combining graph convolutional network and convolutional neural network. Where, to upgrade the detection of malignant lesions in breast mammograms, a new BDR-CNN-GCN method was presented. The presented methodincorporates2 advanced neural networks: (i) graph convolutional network (GCN); (ii) convolutional neural network (CNN). The standard 8-layer convolutional neural network incorporated 2 strategies: (i) batch normalization (BN) (ii) dropout (DO). A rank-based stochastic pooling (RSP) was employed to substitute the traditional max pooling. BDR-CNN was the consolidation of convolutional neural network, batch normalization, dropout, rank-based stochastic pooling. The BDR-CNN was hybridized with 2-layer graph convolutional network, the presented model was used to examine the breast mammograms as 14-way data augmentation mode. Experimental outcomes show the sensitivity 96.20 $\pm$ 2.90%, a specificity 96.00 $\pm$ 2.31% and an accuracy 96.10 $\pm$ 1.60%.

Melekoodappattu et al. [44] have presented the detection and classification of breast cancer from digital mammograms using hybrid extreme learning machine classifier. The collections of appropriate image preprocessing, segmentation, feature extraction, selection, prediction algorithms were significant part of accurate detection with classification of cancer on mammograms. Classification strategies assess unlabeled datasets class labeling depend on its similarity to the pattern learned. The Glowworm Swarm Optimization (GSO) approach was determining multiple solutions, also similar or dissimilar objective function values simultaneously. The feature of Glowworm Swarm Optimization was supported to enhancing the feature set acquired from Multiscale feature extraction process. The problem that arises due to the unconditional output matrix of the hidden phase of Extreme learning machine classifier was poor performance in generalization. The optimization algorithms could deal the issues, because of its global search capacities. Where, Extreme learning machines along Fruit fly Optimization Algorithm including Glowworm Swarm Optimization was suggested for regulating the input weight to attain higher performance in the hidden node of Extreme learning machines. The testing precision with sensitivity of presented method was 100% and 97.91%. The system could identify the calcifications, tumors with 99.15 %accuracy.

Saba et al. [45] have presented recent advancement in cancer detection utilizing machine learning: Systematic survey of decades, comparisons, challenges. Cancer was a deadlydisease caused by genetic disorder aggregation as well as variety of pathological changes. Cancer must rapidly with exactly diagnosed in initial stage for its cure. The modality contains various considerations, via complicated history, improper diagnostics, treatment were major causes of deaths. Several state of art methods were characterized under the same cluster. The outcomes were assessed in benchmark datasets, like accuracy, sensitivity, specificity, false-positive metrics.

- **Research gap**

There several breast cancer classification methods are mentioned in the literature survey [12,36-45], that methods has several limitations such as during classification process the accuracy of the Benign is clearly classify and reduces the accuracy of the malignant, some method does not clearly classify the malignant and Benign and only shows the accuracy of the normal region and the error rate is increased, some methods shows accuracy of the image but the computational complexity is increased.

3. Proposed method

In this section, detection with classification of breast cancer utilizing the Entropy Based Local Binary Pattern (ELBP) based Radiomic features based Feature Extraction Recalling Enhanced Recurrent Neural Network (RERNN) hyper parameter tuned using Lizard Optimization Algorithm (LOA) Approach is proposed. The detailed description of Fig. 1 block diagram is explained below:

3.1. Input acquisition

Here, real time dataset from VPS Lakeshore hospital image consists of 300 images, from this 120 imageries are deemed as training phase, the remaining imageries are deemed as testing phase.

3.2. Preprocessing using Altered phase Preserving Dynamic Range Compression (APPDRC) technique

Here, the real time dataset consists of mammogram X-ray images are captured using X-ray machine and stored in the computer Aided device (CAD). From this the input image contains lot of noises and it diminishes the quality of the images. Then to eliminate the noise as well as increase the quality of the images APPDRC technique is used. The main aim of APPDRC technique is used to filters and to decrease the dynamic ranges of the images. It uses monogenic filters to diminish the noises of the images. Here, mono genic filters have been utilized to attain the local with amplitude phases and it is created by joining the radial band and high pass filters by using Riesz transform. It creates a 2D equivalent with Hilbert transform and it uses 2 filters with the 2D frequency domain such as f_1, f_2 u and the frequency domain equation is given in equation (1)–(2):

$$K_1 = z\frac{f_1}{\sqrt{f_1^2+f_2^2}} \tag{1}$$

$$K_2 = z\frac{f_2}{\sqrt{f_1^2+f_2^2}} \tag{2}$$

here $K = (K_1, K_2)$ is represented as the convolutional kernel with the Riesz transform and defines the spatial representation of the vector. Then to get the local and amplitude data of the image is given as z and then convoluted to high pass filters with g with the two resize transforms are filtered in the form of g, K_1g and K_2g. Then this transforms provide 3 outputs namely, Z^*g, Z^*K_1g and Z^*K_2g where * is represented as the convolutional operation. Then the local amplitude at image location and the input image is represented as (i,j) is given in equation (3):

$$I(i,j) = \sqrt{g(i,j)) + f_1g(i,j)^2 + f_2g(i,j)^2} \tag{3}$$

Then the local phase is given in equation (4):

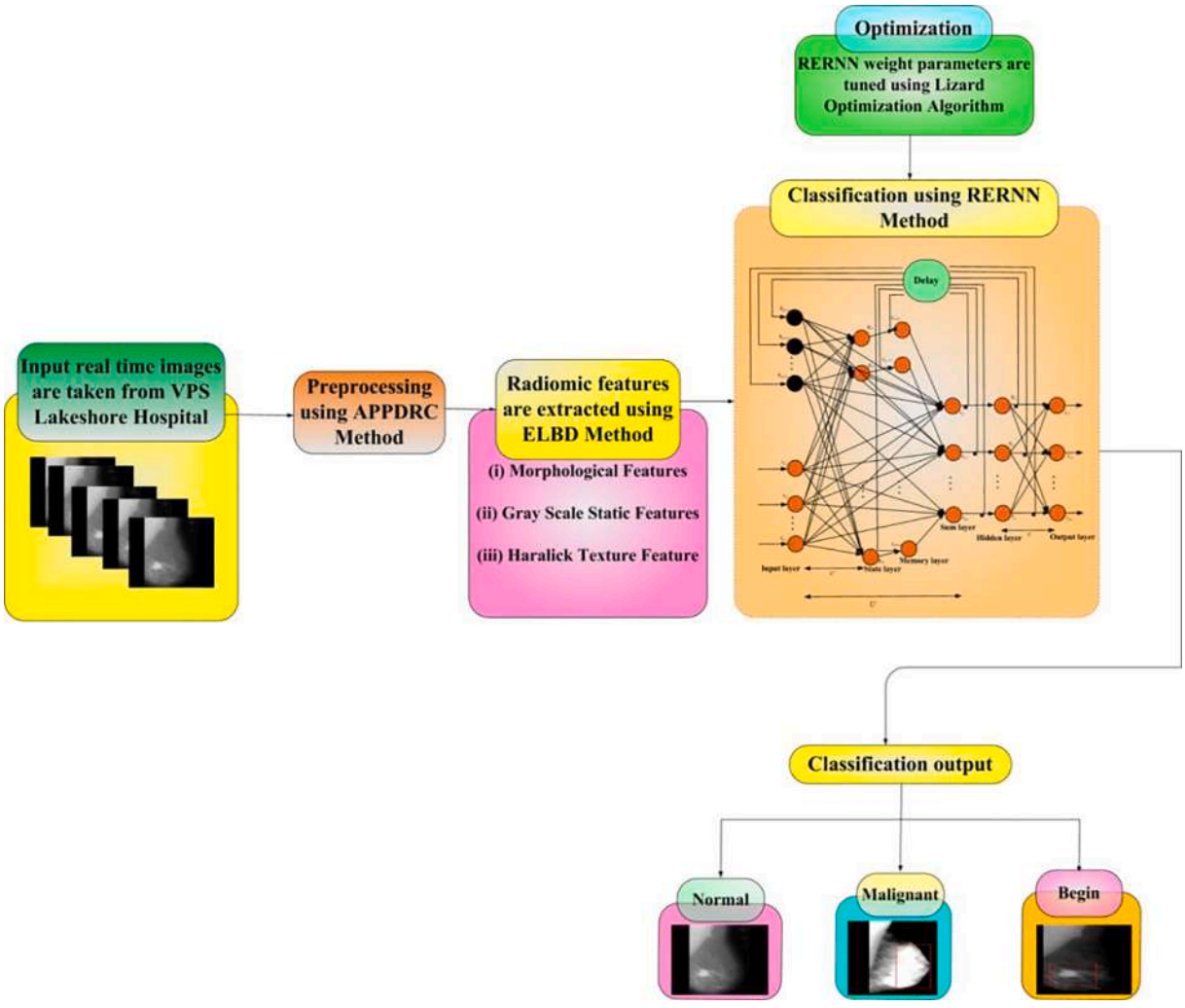

Fig. 1. Block diagram for proposed method.

$$I(i,j) = itan2(g(i,j), \sqrt{g(i,j) + f_1 g(i,j)^2 + f_2 g(i,j)^2}) \quad (4)$$

Then the orientation of the local phase is given in equation (5):

$$\psi(i,j) = itan2(f_2 g(i,j)^2, f_1 g(i,j)) \quad (5)$$

After reconstructed features of filters image is given in equation (6):

$$Y(i,j) = log(I(i,j) + 1).sin(\psi(i,j)) \quad (6)$$

In this the image quality is increased by using the high-pass filters and then provides the fine information's of the image. Here, dynamic range compression mode is used in the high-pass cut off of 1/10000, cut-off spatial frequency of 220 pixels. This method improves the quality of the image by lessening the speckle noises, also decreases the contrast with intensity variations of the input image. Then the radiomic features are extracted using the Entropy Based Local Binary Pattern method.

3.3. Radiomic features are extracted using the Entropy Based Local Binary Pattern (ELBP) method

Radiomic features are extracted by Entropy Based Local Binary Pattern method, radiomic features are used to extract and to analyze the large number of quantitative image features from the medical images. The radiomic features are extracted using the Entropy Based Local Binary Pattern (ELBP) method. The main aim of the feature extraction is to map the m-dimensional images space to less number ofdimensions by applying the Entropy Based Local Binary Pattern method. The radiomic features are utilized to extract the normal and abnormal tissues using machine learning or deep learning approaches. It provides the differentiation of normal and abnormal cells which are not seen to the human eye, and then it will enhance the accuracy to identify the breast cancer in early stage. The less number of dimensional spaces is used to attain the best classification results. Entropy based Local Binary Pattern is used to enhance the performance of feature extraction mode. It computes the information content of every neighborhood pixel, thus the computed entropy contributes as adaptive weight to estimate the information gathered from every neighboring pixel. Then the formulation of feature extracting the Entropy Based Local Binary Pattern method is given in equation (7):

$$ELBP_{RFE}(i,j) = \sum_{k=0}^{k-1} z(f_i - f_j) 2^k \quad (7)$$

where k is represented as the image neighbors with the radius, i,j signifies the co-ordinates of the image pixels with the center of the local region of the image, f_i, f_j is represented as the grey intensity values of the neighboring pixels and the $z(i,j)$ denotes the sampling center of the image pixel is given in equation (8):

$$z(i,j) = \begin{cases} 0, & i,j < 0 \\ 1 & i,j \geqslant 0 \end{cases} \quad (8)$$

The features are extracted in the form of sampling circular form around the central pixels and represented in the form of uniform or in the non-uniform patterns. By using this method breast cancer various radiomic features are extracted. In original Local Binary Pattern, non-uniform patterns are not deemed, because these patterns raised the computational complexity of feature extraction. While utilizing ELBP feature extraction in biometric imageries, the imageries are relatively small, so it does notraise the computational complexity non-uniform patterns. Assuming non-uniform patterns for breast cancer mammogram imageries include more importance to the extraction features, because breast cancer mammogram imageries are unique and differ from one user to another.

Entropy of local absolute variation is applied to create corresponding robust against the changes of local spatial structural. Entropy is a measure of the expected information content or uncertainty of a probability distribution. The use of entropy for feature extraction expressesmoreinformation about the features under consideration. This is because the probability decreases and more information is gained.

In this the radiomic features are classified in several types such as (a) Morphologic features, (b) Gray scale statistic features, (c) Haralick texture features.

3.3.1. Morphologic features

The morphologic features are used to extract the 7 features: 1. Shape, 2. Size, 3. Area, 4. Perimeter, 5. Diameter, 6. Brightness, 7. Compactness.

- **Shape feature**

In this the shape features are used to recognize the object, in this the shape is calculated by taking the ratio of Area and the diameter and the shape equation is given in equation (9):

$$Shape = \frac{A}{(N_D)^2} \quad (9)$$

where A is represented as the area, N_D is represented as the diameter.

3.3.2. Gray scale statistic features

In this Gray scale statistic features are used extract the 4 features: mean, standard deviation, skewness, Kurtosis.

- **Mean**

Mean is calculated by taking average mean pixel value on region of interest and it is used to denote the brightness of the image and the mean equation is given in equation (10):

$$Mean\,(I_m) = \frac{1}{f_i \times f_j} \sum_{A=1}^{f_i} \sum_{B=1}^{f_j} z(i,j) \quad (10)$$

Here i,j denotes co-ordinates of input image pixels with the center of the local region of the image, f_i, f_j is represented as the grey intensity values of the neighboring pixels, $z(i,j)$ denotes sampling center of image pixel.

- **Standard Deviation (SD)**

In this SD is calculated by taking root mean square (RMS) deviation of the values from the arithmetic mean. Then the standard deviation equation is given in equation (11):

$$SD = \sum_{j=1}^{A_i} (\left[i,j(f_{(i)}, f_{(j)})\right] - mean)2 \quad (11)$$

here i,j specifies co-ordinates of the input image pixels with the center of the local region of the image, f_i, f_j is represented as the grey intensity values of the neighboring pixels.

- **Variance**

The variance is defined as the measure of the distance between two or image features are to be extracted and the variance equation is given in equation (12):

$$Variance = \frac{1}{f_i \times f_j} \sum_{i=1}^{f_i} \sum_{j=1}^{f_j} (f(i,j) - mean)^2 \quad (12)$$

3.3.3. Haralick texture features

In this Haralick texture features is used to extract 6 features such as 1. Contrast 2. Correlation, 3. Energy 4. Entropy, 5. Homogeneity, 6. Inertia and 7. In verse different moments.

- **Entropy**

The entropy is used to represent the interference of textural features of the images and the equation is given in equation (13):

$$Entropy(e) = \sum_{i=0}^{m-1}\sum_{j=0}^{n-1}(i-j)^2 log_2 f(i-j) \tag{13}$$

After extracting these features the trained data is given to the Recalling Enhanced Recurrent Neural Network (RERNN) classifier as input recognizing training with testing the classifier performance at the classification of breast cancer imageries as normal and abnormal.

3.4. Breast cancer classification using Recalling Enhanced Recurrent Neural Network (RERNN) classifier

In this section, breast cancer classifications are done using Recalling Enhanced Recurrent Neural Network (RERNN) classifier. In this Recalling Enhanced Recurrent Neural Network (RERNN) classifier is derived from the Elman algorithm with the selective memory features. This classifier is used to classify the images by lessening the error function and tomaximize the speed with high accuracy. The features extracted images are given to RERNNclassifier to classify the images based on training and testing phases. Let us consider the feature extracted images as $\{i_R, j_R\}_{R=1}^{r} \subset \aleph^n \times \wp^z$ are the input trained data is given to the Recalling Enhanced Recurrent Neural Network (RERNN) classifier. Here i_R is represented as the R^{th} input samples and j_R is represented as the output samples. In this Recalling Enhanced Recurrent Neural Network (RERNN) consists of 7 layers to classify the breast cancer images based on normal and abnormal. The various classification layers are explained below:

Here, feature extracted images are given into the input layer. This layer consists of multiple numbers of nodes and the nodes are represented as the $k+l$ linear nodes. Where k is represented as the blank nodes and the input image samples are given into the this blank nodes, the input image samples are given as $i_R = (i_{R1}, i_{R2}, ...i_{Rk})$, l is represented as the black nodes and it is used to mapping the hidden layer output to the delayed vector and it is given as $f_{R-1} = \left(f_{(R-1)_1}, f_{(R-1)_2}, ...f_{(R-1)_l}\right) = \left(f_{R1}, f_{R2}, ...f_{Rk}\right)$, then it is written in the matrix form and the equation is given as $i_R^* = \left(i_{R1}, f_{R-1}\right)^T$, Where $f_0 = 0, R = 1,2,...r$. The output of input layer is given to the state layer. In this state layer is used to give the state values as 0/1 and stored in the memory layer and then the step layer equation is given equation (14):

$$d(.) = \begin{cases} 0, & if\ x_{(R-1)v}\ is\ unimportant \\ 1, & if\ x_{(R-1)v}\ is\ unimportant \end{cases} \tag{14}$$

where $d(.)$ is represented as the state layer with the convolutional activation layer with the training and the testing phases, $x_{(R-1)v}$ is represented as the gradient functions with the memory layer. Then to attain the state layer output with the differentiability and then use the gradient based methods and uses the *logsig* functions. Then the l node is employed in to the *logsig* functions. Then the weight vectorswith the input layer with the x^{th} state layer node with the parameters are given as $q_x^* = \left(q_x^{*j}, q_x^{*f}\right) = \left(q_{x1}^{*j}, q_{x2}^{*j}, ...q_{xl}^{*j}, q_{x(k+1)}^{*jf}, ...q_{x(k+1)}^{*jf}\right)$ and the state layer node parameter equation is given equation (15):

$$d_{Rx} = d\left(q_x^* j_R^*\right) = \frac{1}{1+e^{-q_x^* j_R^*}} = \frac{1}{1+e^{-\left(q_x^* j_R^T + q_x^{*f} f_{R-1}^T\right)}} \tag{15}$$

where $R = 1,2,...,r$, $x = 1,2,...,k$. Consider $Q^* = \begin{bmatrix} q_1^* \\ \cdots \\ q_k^* \end{bmatrix}_{k\times(l+k)}$ is represented as the weight matrix that is connected with the input layer and the state layer with $d_R = (d_{R1}, ...d_{Rk})$.

The output of state layer is given to the memory layer. In this the memory layer is used to store the testing and training data from the previous sum layer and the present state layer and the output of the memory layer is represented as the x^{th} node and its equation is given equation (16):

$$v_{(R-1)}^* = v_{(R-1)} d_{Rx} \tag{16}$$

where $R = 1,2,...,r$, $x = 1,2,...,k$, $v_R = (v_{R1}, v_{R2}, ...v_{Rk})$, then initialize the memory values as $i_0 = (i_{01}, i_{02}, ...i_{0k}) = 0$, this function is represented as the magnitude of the previous sum layer output and then transfers to the next layer and this value is depend on the gate value $d_{Rx} \in (0,1)$ with the function of the state layer. The output of memory layer is given to the sum layer. In this sum layer the nodes collects the data from the memory layer output, present input, and the last recurrent output. Then the sum layer equation with the x^{th} node and its equation are given equation (17):

$$v_{Rx} = \underset{Rx}{\widehat{v}} + v_{(R-1)} d_{Rx} = q_x J_R^* + v_{(R-1)x} d_{Rx} = Q_x^j J_R^T + Q_x^f f_{R-1}^T + V_{(R-1)x} d_{Rx} \tag{17}$$

Where $q_x = \left(q_x^j, q_x^f\right) = \left(q_{x1}^j, q_{x2}^j, ...q_{xl}^j, q_{x(k+1)}^{jf}, ...q_{x(k+1)}^{*jf}\right)$ is represented as the weight vector and connected with the input layer and the x^{th} sum layer node and its equation is given equation (18):

$$\underset{Rx}{\widehat{v}} = q_x J_x^*,\ x = 1,2,....k,\ R = 1,2,...r \tag{18}$$

where $i_{0x} = 0$, consider $Q^* = \begin{bmatrix} q_1^* \\ \cdots \\ q_k^* \end{bmatrix}_{k\times(l+k)}$ is represented as the weight matrix that is connected with the input layer and the sum layer.

There are many number of neurons are present in the Recalling Enhanced Recurrent Neural Network (RERNN) structure from this k number of nodes are hided in the hidden layer and its equation is given equation (19):

$$K_{Rx}^{hidden} = tanf(V_{Rx}) = tan\left(\underset{Rx}{\widehat{V}} + V_{(R-1)} d_{Rx}\right) \tag{19}$$

When $d_{Rx} = 0$, $K_{Rx}^{hidden} = tanf(V_{Rx}) Q_x^j J_R^T + Q_x^f f_{R-1}^T$. From this the *tanf* function performs better than the *logsig* functions.

The delay is noted that the feedback of the present hidden layer output vector and its function is given as $f_R = \left(f_{R1}, f_{R2}, ...f_{Rk}\right)$. Then this function will generate the next input layer and the new input layer is given as $J_R^* \left(J_R, f_{R-1}\right)^T$, then the output layer is determined as $v_R = (v_{R1}, v_{R2}, ...v_{Rk})$, this input and outputs are applied to the memory layer to attain the weight factor. In output node is represented as the z, then the output weight vector is denoted as the $v_w = (v_{1w}, v_{2w}, ...v_{kw})^T \in \aleph^k$ and this layer is connected with the hidden layer with the w^{th} output node, then by combining output in the hidden layer with the whole matrix value is given as $c = (c_1, c_2, ...c_z)_{k\times z}$. Then the activation function of the output layer is given as $d(.)$. Then the output of the RERNN classifier with w^{th} is given as $(w = 1,2,...z)$ and the output equation is given equation (20):

$$i_{Rw} = d(f_R c_w) = f_R c_w \tag{20}$$

where $R = 1,2,...r$, $w = 1,2,...z$ while training the input image the error function is denoted as the R with the R^{th} sample is given equation (21):

$$e_R(f_R c) = \frac{1}{2}\|u_R - i_R\|^2 \tag{21}$$

where $u_R = (u_{R1}, u_{R2}, ..., u_{Rz})$, $y = (q_1, ...q_k, q_1^*, ...q_k^*, c_1^T, ...c_s^T) = \left(q_k^j, q_1^f, ..., q_k^j, q_k^f, ., q_1^{*f}, ...q_k^{*j}, q_k^{*f}, c_1^T, ...c_z^T\right) \in \aleph^{k(2l+2l+z)}$ and $i_R = f_R C = (j_{R1}, j_{R2}, ..., j_{Rz})$, from this R samples are represented as the error function and the error equation is given equation (22):

$$e(y) = \sum_{R=1}^{r} e_R(f_R C) \tag{22}$$

where $R = 1,2,...,r$, $e_R(f_R C)$ is represented as the error function with the R^{th} sample (Breast cancer image), $e(R+1)$ is represented as the error with the $(R+1)^{th}$ samples and then the r is represented as the number of samples. From this the error functions with the weight parameters are R, $j, x, \aleph$ and this error functions are optimized using the Lizard optimization algorithm (LOA).

3.5. Optimized RERNN for detection with classification of Breast cancer utilizing Lizard optimization algorithm (LOA)

The Lizard optimization algorithm (LOA) is used to tune the hyper parameters of the Recalling Enhanced Recurrent Neural Network (RERNN) classifier for getting the optimum parameters. These parameters are tuned for getting more accuracy by reducing the errors and the computational complexity.

Lizard optimization algorithm (LOA) is metaheuristic algorithm; this algorithm uses optimum balance among the exploration and exploitation phases. It is a population based metaheuristic algorithm, in this mating behavior of the lizard is explained with color changing strategies. In this the synergy among the morphs produces the polymorphic population with the self-balance by the subpopulation of every morph without avoiding weak morph. Then the equilibrium has been attained with weak morphs and then forms a smaller subpopulation to maximize its mating behaviors. In this the optimization is acquired by initializing the search agents (lizards) are either produced, eliminates, or transformed by a group of rules in the set of iterations. Since it has its own gain; it takes lesser iteration time than other tuning approach, via grid and random search, then it determine the optimum hyper parameters. The Fig. 2 shows the Flow chart for Recalling Enhanced Recurrent Neural Network with Lizard optimization algorithm (RERNN–LOA) for breast cancer classification. The step-by-step process of Recalling Enhanced Recurrent Neural Network (RERNN) using Lizard optimization algorithm (LOA) are given below

Step 1: Initialization

Initialize the initial population of lizard as $(i_{R1}, i_{R2}, ...i_{Rk})$, and then randomly generates evenly distributed solutions with lower B_L, upper B_U boundaries with the dimensions g. At 1D dimensional search space, the size of the lizard is given by the population size is given as $R_1 \in K$, is

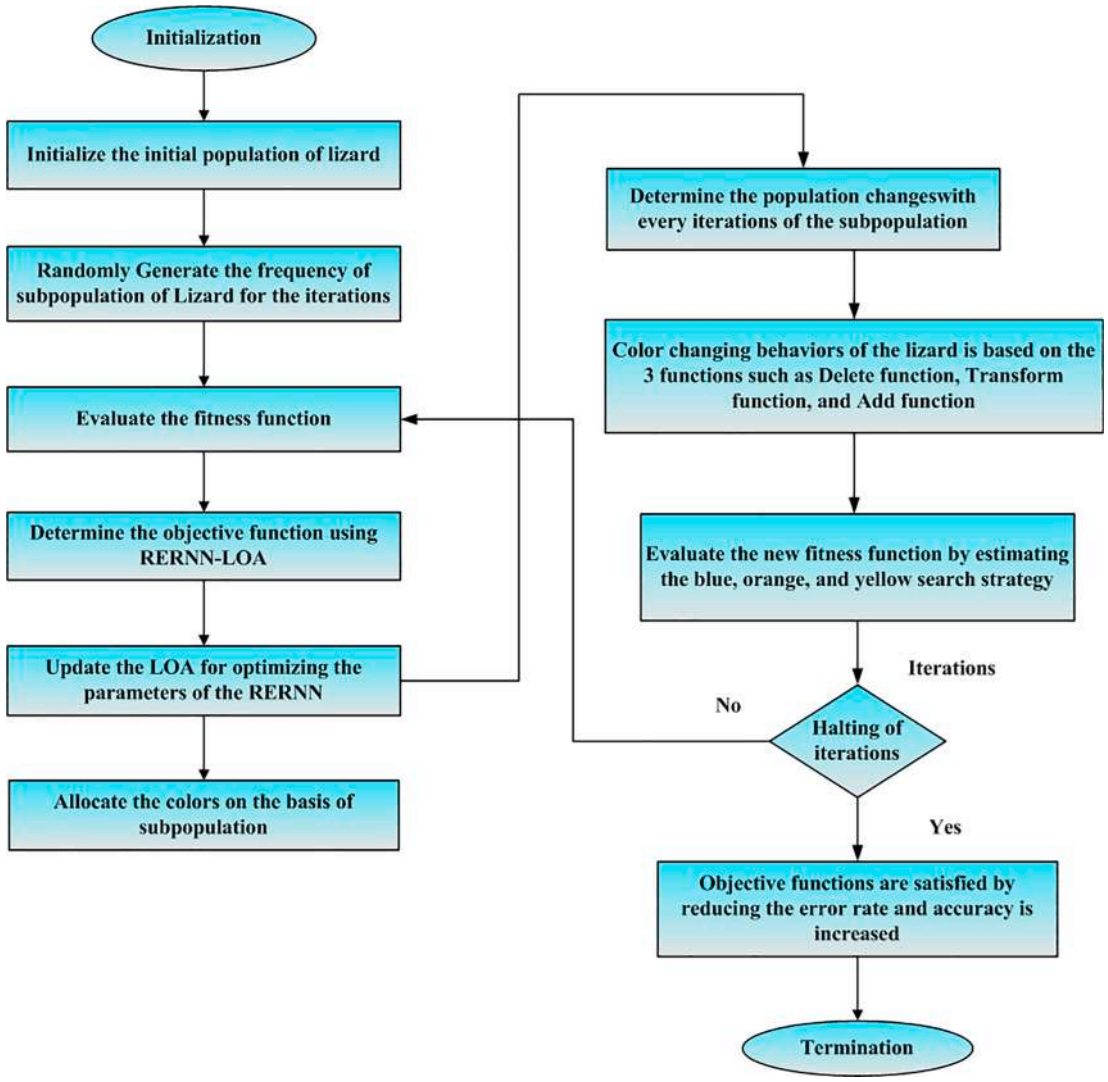

Fig. 2. Flow chart for RERNN -LOA for breast cancer classification.

denoted as the vector of the decision variables and it is given as $\left(i_R^1, i_R^2, \ldots i_R^g\right)$, g is represented as the number of dimensions of the problem, Then the initial population of the mating behavior of the lizard is derived in equation (16) and the equation is given equation (23):

$$i_R^1 = random * \left(B_U^x - B_L^x\right) + B_L^x,\ R = 1, 2, \ldots Lizard_{pop},\ x = 1, 2, \ldots g \tag{23}$$

where *random* is represented as the uniformly distributed random variables in between the [0, 1], and then the upper and the lower bound vectors are given as $\langle B_L^1, B_L^2, \ldots B_L^g \rangle$ to $\langle B_U^1, B_U^2, \ldots B_U^g \rangle$ with the dimension limit.

Step 2: Random Generation

After the procedure of initialization, the input parameters have randomly generated. Then selected the maximal fitness values are depending upon accurate hyper-parameter situation. Here, randomly generate the population of Procedure value for reducing the error rate.

Step 3: Fitness Function

Here, the initial population is produced with the fitness, thenallocates the subpopulation colors, the iterative search procedures are initialized and its ranges start with 1 for maximal iteration count. Here, the fitness function is evaluated to attain the objective function such as reducing the error rate, computational complexity for increasing the accuracy of the breast cancer classification process and to attain the optimum value. In this the weight parameters of the Recalling Enhanced Recurrent Neural Network (RERNN) $(R, j, \aleph)$ are optimized using the Lizard optimization algorithm (LOA). In this the parameters are optimized using the process of population changes, the population changing process consists of three steps for optimizing the Recalling Enhanced Recurrent Neural Network (RERNN) parameters such as Delete function (R), Transform function j, Add function $\aleph$.

Step 4: Updation of position for reducing the error rate and computational complexity and to increase the Accuracy

In this the Lizard optimization algorithm (LOA) explains the mating behavior of the lizard with the total population and the behavior of the iterations are explained in below steps.

Step 5: Subpopulation model is used to reducing the computational complexity

Here, the total number of population is represented as the $Lizard_{Pop}$, the number of seasons is represented as the z, the number of iteration is represented as Max_{iter}, then the amount of the sub population of each iteration is given as $Pop_{blue} \rightarrow blue$, $pop_{orange} \rightarrow orange$, $Pop_{yellow} \rightarrow yellow$ for every populations. In this the computational complexity is reduced by increasing the iterations of the frequency is generated as $\pi * 2$, then the total population is given as $Pop_{Max} = \left(Lizard_{Pop} * 2/subpopul\right) - Pop_{Min}$, Where $subpopul = 3$ with the number of the populations. Then to derive the mating cyclic behavior with the polymorphic populations with the sine functions are represented by the time with the vector of R and starts with the time 0 with the maximum number of iterations using the time space and the frequency is given as $frequency * z$ with the two auxiliary variables such as $A1 = \left[\frac{Pop_{max}}{2}\right] + \left[\frac{Pop_{min}}{2}\right]$ and $A2 = \left[\frac{Pop_{max}}{2}\right] - \left[\frac{Pop_{min}}{2}\right]$, where $A1$ and $A1$ represents the auxiliary variables. Then the subpopulation is represented with each iteration $iter_{pop}$ for reducing the computational complexity equation is given in equation (24):

$$iter_{pop} = A1 + A2 * sin\left\{R + \left[\frac{frequecy}{popsub} * x\right]\right\} \tag{24}$$

where x is represented as the index values from 1 to *popsub* with the total populations of the lizard.

Step 6:Changing the population is used to reduce the error rate

The changes of the populations are evaluated by reducing the error rate by the process ofchanging the colors based on the season with every iterations of the subpopulation. Then the change of the population is given as ΨPop and it subtracts every vector from the subpopulation as $iter_{pop}$ and the final data is $iter_{pop}^{y-1}$ and this function will save the changes in the population vector and its equation is given in equation (25):

$$iter_{pop} = iter_{pop} - iter_{pop}^{y-1} \tag{25}$$

The color changing behaviors of the lizard is based on the 3 functions such as Delete function (R) Transform function j, and Add function $\aleph$.

Step 7: Delete function

In this the delete function is used to match the each lizard population color to neglect the fitness value in the ascending order and it attains the fitness value. From this, the delete function will set the worse value to the initial index of the array and then delete the values in the change of the population in the particular color and minimizes the process till the values attains the 0.

Step 8: Transfer function

Transfer function is the process of the color changes in the population of the previous case decreases and the new population is increases and then saved into the new population.

Step 9: Add function

In this the add function is used to generate the new position within the array and it is used to match the color with the morph of the lizard. For instance the orange lizard will seeks 2 blue lizards, for 1st and 2nd best fitness, and select the random position from 0 to 1 $random_{pop}$ and it represented as the position among the 1st and 2nd lizard, blue lizards utilize yellow as an alternative for adding the yellow lizard. Then, the new position is among the 1st and 2nd best orange lizards equation. By this process the complexity and the error functions are reduced by selection the new population and the reduced error function equation is given in equation (26)

$$\aleph = 1B_L * random_{pop} + 2B_L * \left(1 - random_{pop}\right) \tag{26}$$

Step 10: Search strategiesis used to select the best positions

The search strategies are used minimize the number of particles within the iterations with the behaviors of the blue, orange, yellow strategies are explained. The blue defensive strategies come closer to themselves, then attain the best lizard in the total populations with the fitness function, in this way, the error function is minimized and the minimization of input error function equation is given as

$$R = absolute\left(B_{Lpop} - B_{Lblue}\right) \tag{27}$$

From the above equation the lizards move from one position to the another by the process of new lower bound to the upper bound from the total populations and then the lower and the upper bound equations are given in equation (28)–(29)

$$B_L = B_{Lpop} - R \tag{28}$$

$$B_U = B_{Lpop} - R \tag{29}$$

Then randomly selects the new positions with the lower and the upper bound within the range of 0 and 1 and the minimization of error function equation is given in equation (30)

$$R = \frac{R}{\Psi} \tag{30}$$

where Ψ is represented as the hyper parameter that is calculated from the previous positions and to reduce the input error function of the Recalling Enhanced Recurrent Neural Network (RERNN) classifier. This process is known as the exploitation. Orange dominant expansion strategy is the large territories of the female lizards and then forms the ultra-dominant and prevents them in the attacks. The ultra-dominant process is used to move everywhere in the network. The error functions with the distance is calculated in equation (31)

$$R^k = B_{Lorange} - orange^k \tag{31}$$

From this the gain is calculated by subtracting upper bound and the lower bound with the total number of orange lizards as #orange and the random variables are in between the o and 1 and the gain equation is

given in equation (32)

$$Orange_{gain} = \frac{B_U limit - B_L limit}{\#orange} \tag{32}$$

This new position is known as the exploration and the best position is reached based on the iterations. Its main process is to choosing other lizard territories to attain the best positions. This process will minimizes the output error functions of the RERNN classifier and its equation is givenin equation (33)

$$j^k = j^k + random * \left(orange^l - j^k\right) \tag{33}$$

where, j^k are the yellow lizards which are used to minimize the output error function during exploration and the exploitation process.

Step 11: Termination

Here, the Lizard optimization algorithm (LOA) is utilized to optimize the parameters of the Recalling Enhanced Recurrent Neural Network (RERNN) $(R, j, \aleph)$ classifier and then satisfies the objective functions by increasing the accuracy by reducing error rate and the computational complexity. In this the best iterative positions and the fitness are calculated otherwise repeat the step 3 for getting more values. At one run the subpopulations count of individuals vary in stable rates, and consumes minimal amount of particles to end up by means of two-thirds with maximal population, the remains at the varying time of iterative mode to the entire population count of lizards and remains constant, and allows repeatedly change the balance the search space exploration with exploitation, by search the newly solutions as well as refining the best ones from step 3 till the iterative process termination.

4. Result and discussion

This section describes the simulation result and discussion ofcombining the Advantages of Radiomic features based Feature Extraction and Hyper Parameters tuned recalling enhanced Recurrent Neural Network using Lizard Optimization for Breast cancer Classification. The proposed method is executed in MATLAB site. Then the efficiency of proposed model is examined by evaluation metrics, via error rate, Accuracy, Sensitivity, Specificity, Recall, F-Score, and Precision with various features such as mean, variance, skewness, Standard deviation, Entropy, Kurtosis. Moreover, the proposed method is likened to the existing methods, such as FE-LWT-MFO-ELM, FE-GLCM-FOA-ELM, FE-LBP-Hybrid (BFOA-OPFC) respectively.

4.1. Dataset description

Here, the real time breast cancer images are collected from the VPS hospital [46]. It consists of 300 images. Out of 300 images 90 patients are observed that the cancer diseases are affected in both the breast of women's. In this the four kinds of the diseases are classified namely, Mass, Calcification, Asymmetric, and Distortions and the densities are classified as 1. Entirely fat (Density 1), Scattered fibro glandular densities (Density 2), heterogeneously dense (Density 3), and Extremely dense (Density 4). In this the classification of Benign and malignant images are detected on the basis of mass. Then the mammogram images are classified as 1. Density 1: detected as breast cancer Benign 2. Density 2: breast cancer with malignant, Density 3: Breast cancer mass with Benign, 4. Density 2: breast cancer mass as Benign, 5. Density 3: breast cancer mass as malignant. Here, 120 imageries are deemed as training phase, the remaining imageries are deemed as testing phase.

4.2. Performance metrics

Precision, Recall, F-Measure, Accuracy, Specificity are utilized for measuring the performance metrics. True Negative, True Positive, False Negative, False Positive values are required to measure the confusion matrix.

- True Positive (NN): Breast cancer images are classified as normal as Normal.
- True Negative (NA): Breast cancer images are classified as normal as abnormal.
- False Positive (AA): Breast cancer images are classified as abnormal as abnormal.
- False Negative (AN): Breast cancer images are classified as abnormal as normal.

4.2.1. Precision

This is called Positive predictive values, it is expressed in equation (34).

$$Precesionvalue = \frac{NN}{NN + AN} \tag{34}$$

4.2.2. F-score

It determines utilizing the given equation (35)

$$F - Scorevalue = 2 \times \frac{recall \times precision}{recall + precision} \tag{35}$$

4.2.3. Accuracy

The accuracy is defined as the total number of the classification results values can be determined by the following equation (36)

$$Accuracy = \frac{NN + AN}{AA + AN + NA + NN} \tag{36}$$

4.2.4. Sensitivity

The sensitivity calculates the quantity of actual positives that is correctly predictable. It may be denoted with equation (37).

$$Sensitivity = \frac{NN}{NA + NN} \tag{37}$$

4.2.5. Specificity

This is called true negative rate. It is expressed in equation (38).

$$Specificity = \frac{NA}{NN + NA} \tag{38}$$

4.2.6. Error rate

Error rate may be decided through below equation (39)

$$errorratevalue = 1 - 0.5 \times \frac{Recallvalue + Specificityvalue}{100} \tag{39}$$

4.3. Performance analysis using several methods for Breast cancer classification

Fig. 3 shows the automated detection and Classification breast cancer using real time dataset images from VPS Lakeshore hospital. Then images are pre-processed using APPDRC to remove the noises and to improve the robustness of the images. Then the input images are trained, Features are extracted, using Recalling Enhanced Recurrent Neural Network (RERNN) classifier to classify the breast cancer imageries as normal and abnormal. Then the imageries are classified as Begin and Malignant with more accuracy by reducing the error rate.

4.3.1. Performance analysis using several methods utilized for Breast cancer images

Here, the performance metrics of accuracy, precision, recall, f-measure, Specificity, Sensitivity and the feature extraction methods are Mean, Variance, Standard Deviation, Kurtosis, Entropy, Skewness of the various breast cancer methods are analyzed. Then the proposed feature extraction and classification methods FE-APPDRC-ELBP-RERNN-LOA are likened to the existing feature extraction and classification

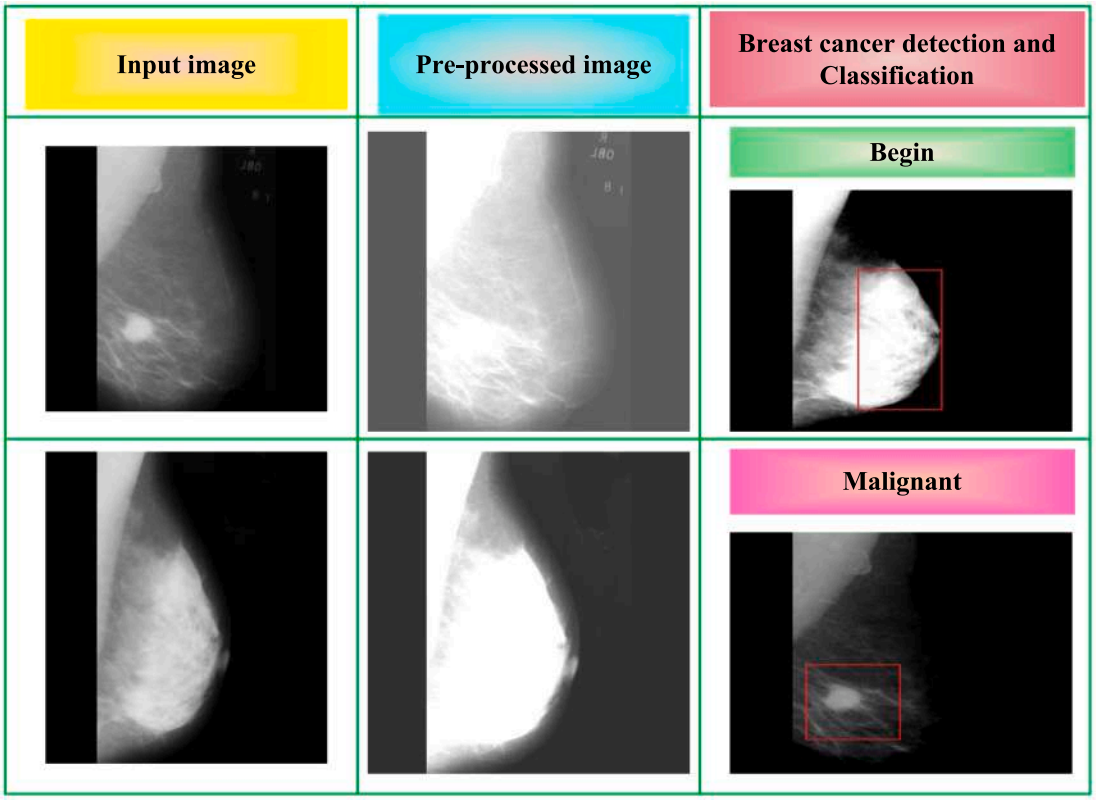

Fig. 3. Automated detection and Classification Breast cancer image (Begin and Malignant).

methods, such as FE-LWT-MFO-ELM [36], FE-GLCM-FOA-ELM [37], FE-LBP-Hybrid (BFOA-OPFC) [38]FE-GLCM-Hybrid CNNRNN-FC-CSO [41], FE-BDR-CNN-GCN [44] and FE-GSO-Hybrid ELM-FOA [43] respectively.

4.3.2. Discussion/Justification of proposed model

Table 1 represents the training and testing of the Breast cancer, Here, the performance of the Accuracy of the proposed FE-APPDRC-ELBP-RERNN-LOA for breast cancer is calculated and the performances are compared with various existing method such as FE-LWT-MFO-ELM, FE-GLCM-FOA-ELM, FE-LBP-Hybrid BFOA-OPFC, FE-GLCM-Hybrid CNNRNN-FC-CSO, FE-BDR-CNN-GCN and FE-GSO-Hybrid ELM-FOA respectively. For Benign analysis, the Accuracy of the proposed method shows 24.76%, 28.97%, 34.75%, 15.52%, 39.01% and 37.08% higher than the existing methods. For malignant analysis, the Accuracy of the proposed method shows 32.75%, 37.86%, 36.21%, 17.72%, 35.5% and 27.05% greater than the existing models. For normal analysis, the Accuracy of the proposed method shows 48.75%, 27.75%, 39.97%, 18.05%, 31.39% and 34.69% higher than the existing methods.

Here, the performance of the F-Score of the proposed FE-APPDRC-ELBP-RERNN-LOA for breast cancer is calculated and the performances are compared with various existing method such as FE-LWT-MFO-ELM, FE-GLCM-FOA-ELM, FE-LBP-Hybrid BFOA-OPFC, FE-GLCM-Hybrid CNNRNN-FC-CSO, FE-BDR-CNN-GCN and FE-GSO-Hybrid ELM-FOA respectively. For Benign analysis, the F-Score of the proposed method shows 37.97%, 54.75%, 29.97%, 24.51%, 27.9% and 22.86% higher than the existing methods For malignant analysis, the F-Score of the proposed method shows 38.86%, 25.36%, 36.75%, 27.56%, 29.65% and 31.24% greater than the existing models. For normal analysis, the F-Score of the proposed method shows 39.65%, 27.96%, 27.97%, 28.45%, 21.56% and 28.34% higher than the existing methods.

Then the performance of the precision of the proposed FE-APPDRC-ELBP-RERNN-LOA for breast cancer is calculated and the performances are compared with various existing method such as FE-LWT-MFO-ELM, FE-GLCM-FOA-ELM, FE-LBP-Hybrid BFOA-OPFC, FE-GLCM-Hybrid CNNRNN-FC-CSO, FE-BDR-CNN-GCN and FE-GSO-Hybrid ELM-FOA respectively. For Benign analysis, the precision of the proposed method shows 28.94%, 39.02%, 21.46%, 24.65%, 33.54% and 29.31% higher than the existing methods. For malignant analysis, theprecision of the proposed method shows 32.74%, 59.94%, 43.73%, 47.54%, 39.87% and 51.35% greater than the existing models. For normal analysis, the precision of the proposed method shows 26.74%, 45.45%, 26.75%, 41.75%, 27.39% and 36.83% higher than the existing methods.

Then the performance of the Sensitivity of the proposed FE-APPDRC-ELBP-RERNN-LOA for breast cancer is calculated and the performances are compared with various existing method such as FE-LWT-MFO-ELM, FE-GLCM-FOA-ELM, FE-LBP-Hybrid BFOA-OPFC, FE-GLCM-Hybrid CNNRNN-FC-CSO, FE-BDR-CNN-GCN and FE-GSO-Hybrid ELM-FOA respectively. For Benign analysis, the Sensitivity of the proposed method shows 45.64%, 37.86%, 36.86%, 32.61%, 27.83% and 42.09% higher than the existing methods. For malignant analysis, the Sensitivity of the proposed method shows 37.86%, 49.97%, 37.73%, 37.94%, 36.42% and 42.74% greater than the existing models. For normal analysis, the Sensitivity of the proposed method shows 27.97%, 36.32%, 30.07%, 29.64%, 35.06% and 37.13% higher than the existing methods.

Then the performance of the Specificity of the proposed FE-APPDRC-ELBP-RERNN-LOA for breast cancer is calculated and the performances are compared with various existing method such as FE-LWT-MFO-ELM, FE-GLCM-FOA-ELM, FE-LBP-Hybrid BFOA-OPFC, FE-GLCM-Hybrid CNNRNN-FC-CSO, FE-BDR-CNN-GCN and FE-GSO-Hybrid ELM-FOA respectively. For Benign analysis, the Specificity of the proposed method shows 37.53%, 29.02%, 32.94%, 31.04%, 28.64% and 36.53% higher than the existing methods. For malignant analysis, the Specificity of the proposed method shows 42.53%, 25.86%, 38.85%, 32.93%, 37.45% and 29.36% greater than the existing models. For normal analysis, the Mean of the proposed method shows 36.97%, 54.86%, 43.97%, 42.65%, 38.62% and 41.76% higher than the existing methods.

Here, the performance of the Standard Deviation of the proposed FE-

Table 1
Training and Testing Result for Automated detection and Classification Breast cancer images.

Performance metrics		Method with optimization algorithm						
		FE-LWT-MFO-ELM	FE-GLCM-FOA-ELM	FE-LBP-Hybrid BFOA-OPFC	FE-GLCM-Hybrid CNNRNN-FC-CSO	FE-BDR-CNN-GCN	FE-GSO-Hybrid ELM-FOA	FE-APPDRC-ELBP-RERNN-LOA (Proposed)
Accuracy	Normal	86.47%	75.97%	68.75%	86.45%	71/0.84%	72.85%	99.87%
	Malignant	85.86%	74.64%	69.35%	84.65%	73.54%	78.43%	99.65%
	Benign	84.54%	76.46%	63.24%	82.64%	74.25%	72.43%	97.56%
F-Score	Normal	78.76%	74.97%	73.97%	75.87%	73.86%	76.89%	94.47%
	Malignant	74.96%	76.84%	76.43%	76.65%	71.43%	78.46%	95.36%
	Benign	76.36%	74.95%	75.43%	74.86%	76.23%	79.36%	95.97%
Precision	Normal	65.85%	60.86%	75.86%	77.65%	84.86%	81.54%	92.55%
	Malignant	64.62%	61.98%	76.85%	75.35%	83.74%	84.54%	93.55%
	Benign	63.85%	63.52%	77.23%	76.21%	85.34%	83.56%	96.34%
Sensitivity	Normal	67.97%	77.75%	69.97%	73.65%	78.56%	81.25%	87.96%
	Malignant	67.28%	78.46%	63.75%	74.75%	78.23%	80.24%	86.78%
	Benign	66.85%	76.36%	69.82%	74.98%	79.21%	83.875	87.67%
Specificity	Normal	76.97%	68.97%	67.97%	73.64%	77.85%	81.67%	93.56%
	Malignant	76.56%	67.46%	68.45%	74.67%	76.94%	82.57%	93.57%
	Benign	77.94%	67.94%	67.98%	73.84%	77.39%	81.57%	94.53%
Error rate	Normal	0.0034	0.0043	0.0042	0.0052	0.0037	0.0047	0.0012
	Malignant	0.0033	0.0044	0.0043	0.0053	0.0036	0.0045	0.0013
	Benign	0.0031	0.0042	0.0041	0.0052	0.0038	0.0043	0.0014
Standard Deviation	Normal	0.82%	0.78%	0.63%	0.74%	0.81%	0.78%	0.93%
	Malignant	0.77%	0.84%	0.62%	0.71%	0.86%	0.81%	0.96%
	Benign	0.87%	0.69%	0.76%	0.72%	0.83%	0.82%	0.98%
Variance	Normal	0.82%	0.79%	0.75%	0.72%	0.86%	0.79%	0.92%
	Malignant	0.76%	0.81%	0.65%	0.75%	0.85%	0.81%	0.97%
	Benign	0.85%	0.67%	0.72%	0.71%	0.84%	0.77%	0.98%
Mean	Normal	0.82%	0.71%	0.77%	0.72%	0.77%	0.73%	0.96%
	Malignant	0.84%	0.73%	0.65%	0.76%	0.79%	0.84%	0.97%
	Benign	0.71%	0.72%	0.83%	0.73%	0.76%	0.82%	0.98%
Skewness	Normal	0.75%	0.84%	0.71%	0.64%	0.86%	0.76%	0.96%
	Malignant	0.69%	0.87%	0.61%	0.63%	0.82%	0.74%	0.89%
	Benign	0.79%	0.75%	0.67%	0.66%	0.81%	0.78%	0.95%
Kurtosis	Normal	0.75%	0.84%	0.69%	0.71%	0.79%	0.86%	0.93%
	Malignant	0.71%	0.79%	0.62%	0.69%	0.83%	0.88%	0.96%
	Benign	0.81%	0.72%	0.63%	0.72%	0.81%	0.76%	0.88%
Entropy	Normal	0.82%	0.74%	0.63%	0.69%	0.82%	0.83%	0.97%
	Malignant	0.75%	0.81%	0.64%	0.78%	0.86%	0.77%	0.95%
	Benign	0.85%	0.76%	0.67%	0.71%	0.78%	0.79%	0.96%
Recall	Normal	0.87%	0.75%	0.82%	0.83%	0.89%	0.88%	0.97%
	Malignant	0.73%	0.81%	0.79%	0.74%	0.82%	0.83%	0.92%
	Benign	0.82%	0.77%	0.83%	0.77%	0.79%	0.81%	0.95%

APPDRC-ELBP-RERNN-LOA for breast cancer is calculated and the performances are compared with various existing method such as FE-LWT-MFO-ELM, FE-GLCM-FOA-ELM, FE-LBP-Hybrid BFOA-OPFC, FE-GLCM-Hybrid CNNRNN-FC-CSO, FE-BDR-CNN-GCN and FE-GSO-Hybrid ELM-FOA respectively. For Benign analysis, the Standard Deviation of the proposed method shows 43.65%, 38.97%, 38.97%, 37.54%, 38.24% and 41.64% higher than the existing methods. For malignant analysis, the Standard Deviation, of the proposed method shows 46.86%, 38.97%, 38.97%, 42.74%, 36.82% and 43.63% greater than the existing models. For normal analysis, the Standard Deviation of the proposed method shows 56.86%, 53.86%, 32.86%, 55.64%, 47.34% and 34.71% higher than the existing methods.

Then the performance of the variance of the proposed FE-APPDRC-ELBP-RERNN-LOA for breast cancer is calculated and the performances are compared with various existing method such as FE-LWT-MFO-ELM, FE-GLCM-FOA-ELM, FE-LBP-Hybrid BFOA-OPFC, FE-GLCM-Hybrid CNNRNN-FC-CSO, FE-BDR-CNN-GCN and FE-GSO-Hybrid ELM-FOA respectively. For Benign analysis, the variance of the proposed method shows 34.75%, 56.86%, 37.75%, 36.43%, 29.56% and 47.35% higher than the existing methods. For malignant analysis, the-variance of the proposed method shows 36.75%, 43.67%, 33.64%, 34.97%, 46.12% and 39.52% greater than the existing models. For normal analysis, the variance of the proposed method shows 54.75%, 37.86%, 43.76%, 51.09%, 47.83% and 52.81% higher than the existing methods.

Then the performance of the Mean, of the proposed FE-APPDRC-ELBP-RERNN-LOA for breast cancer is calculated and the performances are compared with various existing method such as FE-LWT-MFO-ELM, FE-GLCM-FOA-ELM, FE-LBP-Hybrid BFOA-OPFC, FE-GLCM-Hybrid CNNRNN-FC-CSO, FE-BDR-CNN-GCN and FE-GSO-Hybrid ELM-FOA respectively. For Benign analysis, the Mean of the proposed method shows 37.76%, 46.87%, 49.86%, 41.65%, 39.05% and 42.73% higher than the existing methods. For malignant analysis, the Mean, of the proposed method shows 44.65%, 38.65%, 36.86%, 32.84%, 41.87% and 39.02% greater than the existing models. For normal analysis, the Mean of the proposed method shows 35.75%, 38.86%, 54.75%, 43.85%, 41.25% and 37.65% higher than the existing methods.

Here, the performance of the Skewness, of the proposed FE-APPDRC-ELBP-RERNN-LOA for breast cancer is calculated and the performances are compared with various existing method such as FE-LWT-MFO-ELM, FE-GLCM-FOA-ELM, FE-LBP-Hybrid BFOA-OPFC, FE-GLCM-Hybrid CNNRNN-FC-CSO, FE-BDR-CNN-GCN and FE-GSO-Hybrid ELM-FOA respectively. For Benign analysis, the Skewness of the proposed method shows 36.97%, 45.76%, 37.86%, 38.64%, 39.04% and 42.73% higher than the existing methods. For malignant analysis, the Skewness of the proposed method shows 36.86%, 45.86%, 36.86%, 37.62%, 47.63% and 39.74% greater than the existing models. For normal analysis, the Skewness of the proposed method shows 38.75%, 43.86%, 37.86%, 46.86%, 36.27% and 38.43% higher than the existing methods.

Then the performance of Kurtosis of the proposed FE-APPDRC-ELBP-RERNN-LOA for breast cancer is calculated and the performances are

compared with various existing method such as FE-LWT-MFO-ELM, FE-GLCM-FOA-ELM, FE-LBP-Hybrid BFOA-OPFC, FE-GLCM-Hybrid CNNRNN-FC-CSO, FE-BDR-CNN-GCN and FE-GSO-Hybrid ELM-FOA respectively. For Benign analysis, the Kurtosis of the proposed method shows 36.86%, 45.75%, 39.75%, 33.85%, 41.04% and 38.46% higher than the existing methods. For malignant analysis, the Kurtosis of the proposed method shows 53.75%, 48.97%, 35.86%, 47.93%, 41.75% and 50.32% greater than the existing models. For normal analysis, the Kurtosis of the proposed method shows 37.97%, 54.86%, 46.86%, 44.06%, 39.64% and 47.63% higher than the existing methods.

Then the performance of the Entropy of the proposed FE-APPDRC-ELBP-RERNN-LOA for breast cancer is calculated and the performances are compared with various existing method such as FE-LWT-MFO-ELM, FE-GLCM-FOA-ELM, FE-LBP-Hybrid BFOA-OPFC, FE-GLCM-Hybrid CNNRNN-FC-CSO, FE-BDR-CNN-GCN and FE-GSO-Hybrid ELM-FOA respectively. For Benign analysis, the Entropy of the proposed method shows 25.74%, 32.32%, 36.75%, 33.85%, 38.03% and 28.64% higher than the existing methods. For malignant analysis, the Entropy, of the proposed method shows 26.86%, 43.86%, 42.86%, 44.73%, 39.74% and 37.84% greater than the existing models. For normal analysis, the Mean of the proposed method shows 32.75%, 29.07%, 31.96%, 29.74%, 35.45% and 32.71% higher than the existing models.

Then the performance of the Recall of the proposed FE-APPDRC-ELBP-RERNN-LOA for breast cancer is calculated and the performances are compared with various existing method such as FE-LWT-MFO-ELM, FE-GLCM-FOA-ELM, FE-LBP-Hybrid BFOA-OPFC, FE-GLCM-Hybrid CNNRNN-FC-CSO, FE-BDR-CNN-GCN and FE-GSO-Hybrid ELM-FOA respectively. For Benign analysis, the Recall of the proposed method shows 37.97%, 28.96%, 24.97%, 32.84%, 38.42% and 29.53% higher than the existing methods. For malignant analysis, the Recall, of the proposed method shows 37.86%, 52.46%, 53.83%, 47.78%, 51.62% and 49.43% greater than the existing models. For normal analysis, the Recall of the proposed method shows 28.84%, 37.74%, 63.42%, 56.82%, 57.54% and 39.03% higher than the existing methods FE-LWT-MFO-ELM, FE-GLCM-FOA-ELM, FE-LBP-Hybrid BFOA-OPFC, FE-GLCM-Hybrid CNNRNN-FC-CSO, FE-BDR-CNN-GCN and FE-GSO-Hybrid ELM-FOA respectively.

Then the performance of the Error rate of the proposed FE-APPDRC-ELBP-RERNN-LOA for breast cancer is calculated and the performances are compared with various existing method such as FE-LWT-MFO-ELM, FE-GLCM-FOA-ELM, FE-LBP-Hybrid BFOA-OPFC, FE-GLCM-Hybrid CNNRNN-FC-CSO, FE-BDR-CNN-GCN and FE-GSO-Hybrid ELM-FOA respectively. For Benign analysis, the Recall of the proposed method shows 34.66%, 26.86%, 38.976%, 43.75%, 26.86% and 30.97% lower than the existing methods. For malignant analysis, the Error rate, of the proposed method shows 34.86%, 27.97%, 43.87%, 28.97%, 29.08% and 36.87% lower than the existing models. For normal analysis, the Error rate of the proposed method shows 27.87%, 20.97%, 25.76%, 43.75%, 36.86% and 27.97% lower than the existing methods FE-LWT-MFO-ELM, FE-GLCM-FOA-ELM, FE-LBP-Hybrid BFOA-OPFC, FE-GLCM-Hybrid CNNRNN-FC-CSO, FE-BDR-CNN-GCN and FE-GSO-Hybrid ELM-FOA respectively.

Fig. 4 represents the Performance metrics of ROC performance of Radiomic features of breast cancer images from real time dataset. Here, the ROC (Receiver Operating Characteristics) curve multiple features with real time Breast cancer image for the curve for the 14 features of the breast images. It is calculated on the basis of the total number of the true positive rate is divides the total number of the false positive rate. In this the values are determined by the process of features between the values 0.0 and 1.0. TPR is defined as the proportion of positive data points that are correctly predicted as positive.

5. Conclusion

This paper proposes, combining the Advantages of Radiomic features based Feature Extraction and Hyper Parameters tuned Recalling Enhanced Recurrent Neural Network (RERNN) using Lizard

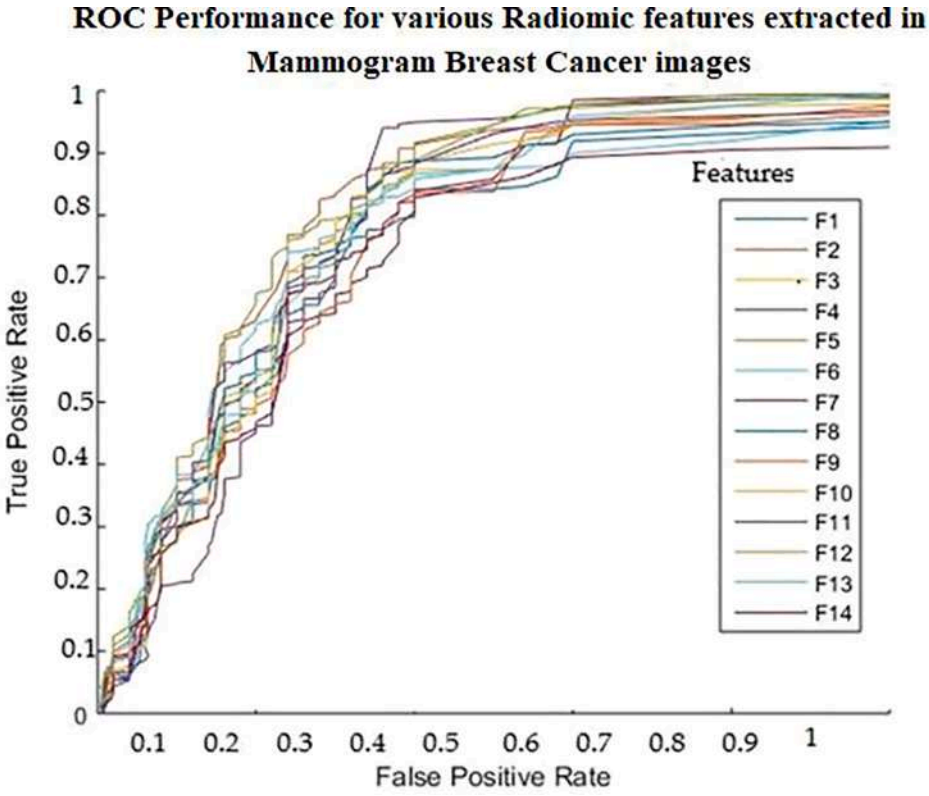

Fig. 4. Performance metrics ROC performance of Radiomic features.

optimization algorithm (LOA) for Breast cancer Classification. This method was successes fully provided the misclassification errors during the classification process on screening the breast cancer mammogram images. And this method was applicable in real time applications for screening the abnormalities of the breast cancer in starting stage, thus, determining the proper treatment to be given to the patient for decreasing deaths caused by breast cancer. The simulation process is executed in the MATLAB platform. The proposed FE-APPDRC-ELBP-RERNN-LOA attains Precision is 34.65%, 26.45%, 33.46%, Sensitivity 45.36%, 33.45%, 47.56%, Specificity 37.42%, 38.54%, 28.47%, 27.48% higher than the existing methods, such as FE-LWT-MFO-ELM, FE-GLCM-FOA-ELM, FE-LBP-Hybrid BFOA-OPFC, FE-GLCM-Hybrid CNNRNN-FC-CSO, FE- BDR-CNN-GCN and FE-GSO-Hybrid ELM-FOA respectively. The limitation of this work is that, the classification efficiency of the proposed model is proportional to the number of training images; a small image dataset will affect its performance. However, the proposed method achieves high classification efficiency on a large image dataset but expensive in computational cost. The breast cancer can be localized weakly, so to improve the accuracy with less computational cost future work is suggested.

In the future work, incorporating more than one classifier with feature selection techniques to enhance the classification accuracy of the proposed work and to examine the selective classifier mode.

6. Data availability statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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CRediT authorship contribution statement

S. Subasree: Supervision. **N.K. Sakthivel:** Conceptualization, Methodology, Writing – original draft. **Khushboo Tripathi:** Supervision. **Deepshikha Agarwal:** Supervision. **Amit Kumar Tyagi:** Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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