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Deep Segmentation and Classification for Breast Cancer Detection in Mammogram Images

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Abstract

Breast cancer is one of the most serious diseases, with the highest occurrence worldwide, where early identification and diagnosis, obtained by imaging techniques such as mammography, play a vital role in preventing the disease. For mammography diagnostics, radiologists have a high false positive rate and an accuracy of roughly 82 percent. Deep learning (DL) approaches have demonstrated promising results in developing computer-aided diagnostic (CAD) systems for early identification of breast cancer.Using mammogram images, this research develops a new deep segmentation with residual network (DS-RN) based breast cancer diagnosis model. Pre-processing, Faster Region based Convolution Neural Network (R-CNN) (Faster R-CNN), and Inception v2 model based segmentation, feature extraction, and classification are all part of the described DS-RN model. Random forest (RF) classifier model is used to classify mammogram images. To ensure that the provided model performs better on the Mini-MIAS dataset, a rigorous simulation process is used. The DS-RN model achieved maximum classification performance with sensitivity, specificity, accuracy, and F-Measure of 96.36%, 100 %, 97.75%, and 98.15%, respectively, according to the collected experimental values.

Keywords: Breast cancer, Classification, Segmentation, Feature extraction, Mammogram

1. Introduction

Breast cancer is a prevalent type of cancer that affects women. Usually, breast cancer consumes maximum time for developing and signs expressed latter. There is no cure for cancer, however it can be treated to extend one's life if detected early enough. As a result, the American Cancer Society (ACS) recommends a previous breast cancer prediction, stating that a screening test is critical for extending one's life expectancy [1].

Mammogram screening models have recently been widely used in digitalized diagnostic systems to classify breast lesions. For detecting cancers in digital mammogram images, most Computer Aided Diagnosis (CAD) models rely on Machine Learning (ML) approaches. For classifying images into many classes, these approaches should be determined with a variety of descriptive features.

Several developers offered mammogramimages for 2-class (normal and abnormal) classification and achieved a successful simulation result. Mazurowski et al. [2] created a template based on a breast tumour prediction model. The data collection is based on a large number of Digital Database for Screening Mammography (DDSM) images and is extremely accurate. Wei et al. [3] used a data set of huge pictures to build a relevant feedback learning strategy and execute classification using the SVM radial kernel. Tao et al. [4] linked the function of two classification models, curvature scale space and local linear embedded metric, to the use of a database and the accuracy of two classifiers. For 2-class classification of digital mammograms, Abirami et al. [5] used wavelet features, which achieved the highest accuracy for the Mammographic Images Analysis Society (MIAS) data set.

Elter and Halmeyer [6] performed classification using Artificial Neural Network (ANN) and Euclidean metric classification, respectively, and achieved a higher level of performance. The developers used a two-class classification system; nevertheless, this is insufficient to prevent unnecessary biopsy because tumours can be benign or malignant in atypical circumstance. The Extreme Learning Machine (ELM) model was presented by Suckling [7] for categorising mammograms in the MIAS database. The newly constructed model has outperformed other models based on the same database.On the basis of wavelet analysis and Artificial Neural Networks, Jasmine et al. [8] performed 2-class classification with the projected model (ANN). This method was calculated using the MIAS database and yielded higher accuracy. Xu et al. [9] linked the function of three neural networks (NNs) to the recommended Multilayer Perceptron (MLP) function as the number of features increased. With the use of mammogram scans, the model was able to achieve better accuracy.

Deep Learning (DL) under the application of NN has been supported as state-of-the-art outcomes in enormous computer vision models, such as object prediction and classification, in recent decades. DL techniques are employed in a variety of clinical imaging applications, including histopathology tissue categorization and histology pictures. As a result, only a few researchs are available when using DL to categorise mammogramimages. In [10] Convolutional Neural Network (CNN) was used to segment mammographic texture breast tissue. Breast density measurements have been calculated using multi-scale features and auto-encoders (AE). However, the data set is small sized, thus CNNs are used to classify micro-calcifications.Mert et al. [11] created a 2-class categorization radial basis function neural network (RBFNN) with independent component analysis (ICA). On the WBDC data set with huge images, maximum accuracy was achieved. Dheeba et al. [12] employed particle swarm optimization (PSO)-based Wavelet Neural Network (PSO-WNN) and deep belief network (DBN) appropriately for 2-class classification and achieved effective results on a data set comprising images.

This research proposes a unique deep segmentation with residual network (DS-RN) related breast cancer analysis approachwith the help of mammogram images. Preprocessing, faster region-based convolution neural network (R-CNN) (Faster R-CNN) with Inception v2 model-based segmentation, feature extraction, and classification make up the proposed DS-RN technique. Decision tree (DT) and random forest (RF) classification algorithms were used to classify the mammography images. On the Mini-MIAS dataset, a quick simulation is run to confirm that the proposed technique is progressing.

2. Proposed method

The processes involved in the provided model are depicted in Fig. 1. The input mammogramimage is preprocessed and then segmented using the Faster RCNN model, as seen in the figure. Furthermore, the ResNet model is used as a feature extraction model to extract an usable set of feature vectors from a segmented image. Finally, an RF model performs the categorization procedure.

2.1. Preprocessing

The preprocessing stage is used in this strategy to improve the classification process's results. To remove noise from the image, the input image is first fed into a mean shift filtering technique. The extracted image is then thresholded and converted to binary format. The outlines of the items in the imsges are then retrieved using a contour sketching step. Then, using mask generation, a higher contour mask is used to retain a large object. In addition, the mask's noise is eliminated, and the contrast enhancement is calculated using the Contrast Limited Adaptive Histogram Equalization (CLAHE) method. Finally, when the preprocessed image is sent into image segmentation, the contrast is improved.

2.2. DL based Segmentation Process

For classifying and preparing images, a DL-based Faster RCNN with the Inception v2 approach is used. For training the ROI, this model is first trained with human-modeled images. A segmentation model was used to detect the impacted area in the new test image based on the training phase. RCNN is a method for predicting objects that was created with two goals in mind. The regions are supposed to be the primary stages of deep fully convolutional networks, whereas the Fast R-CNN predictor uses the prior regions. The entire procedure is collected in a single network in the case of object prediction. The Fast R-CNN method uses NN units to convert data about RPN.

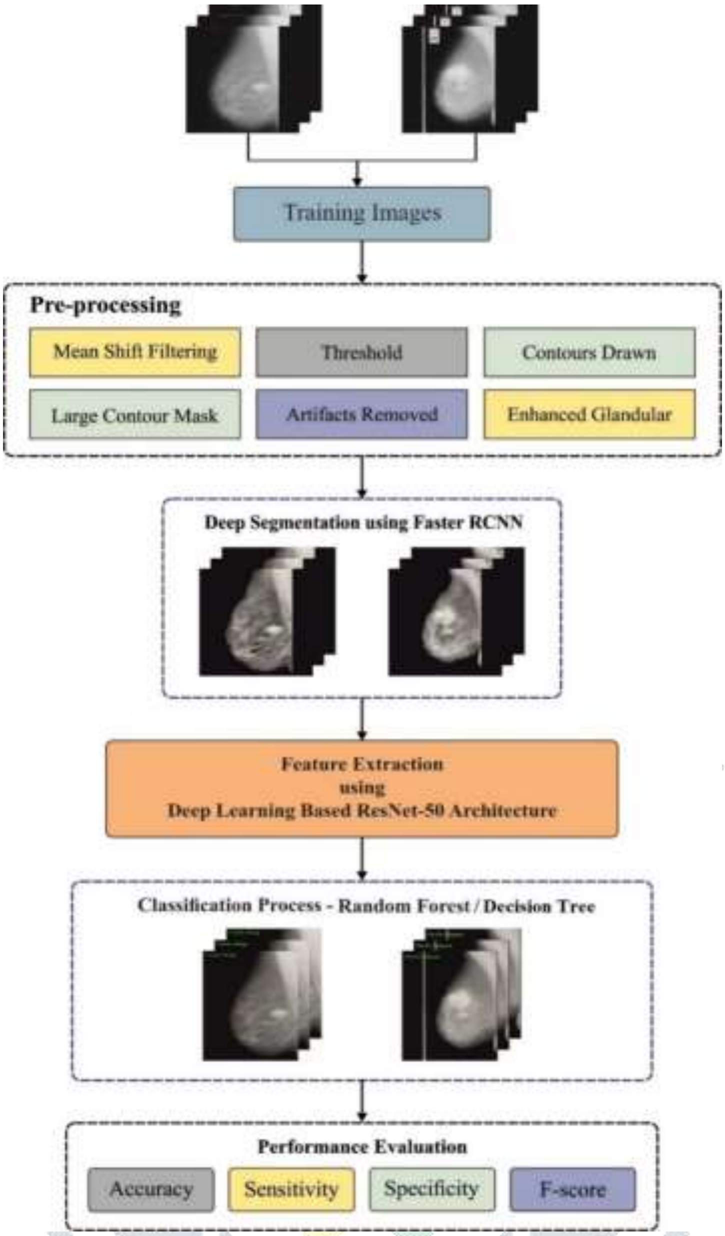


Fig. 1. Block diagram of presented model

2.3. ResNet 50 based feature extraction

CNN has recently dominated the complete visual space. An input layer, an output layer, and several hidden layers make up a CNN. Convolutional layers, pooling layers, fully connected (FC) layers, and normalisation layers are typically found in CNN's hidden layers (ReLU). For time-consuming techniques, extra layers are used. The CNN structure has proven to be quite useful in a variety of computer vision and machine learning problems. The prediction and training operations are computed at an abstract level by CNN, with the remaining specifics in the subparagraphs.Because of its record-breaking processing performance, the CNN approach is frequently used in smart ML fields. The performance of CNN is critical to linear algebra. Matrix vector multiplication is central premises of how data and weights are displayed. For each image collection, the layers are made up of numerous features. When a face image is given to CNN as an input, the system will learn basic attributes such as edges, bright spots, dark areas, forms, and so on. The next set of layers consists of forms and objects that are linked to recognizable visuals, such as eyes, noses and mouth.The following layer is made up of components that are similar to the original faces. In addition, the network's shapes and objects can be used to define human faces. CNN divides the image categorization process into small chunks rather than mapping the complete image.

The features extraction using CNN for estimation is depicted using a 3 X 3 grid. Filtering is the next task, which lines the feature with an image patch. The element is improved by employing the appropriate feature pixel, and the procedure is finished and classified by the total number of pixels in feature space. Within the feature patch, the resultant value for a feature is fixed. This is followed by residual feature patches and attempts in every possible match-repeated field of the filter, which is known as convolution.The next layer of a CNN is supposed to have "max pooling," which helps to reduce the picture stack. Window size must be determined before pooling an image, and the stride must be described. The window is filtered in steps over the image, with the maximum value kept for each window. Max pooling reduces the dimensionality of a feature map while preserving the important information. Rectified Linear Unit (ReLU) is the normalisation layer of a CNN, and it contributes the negative values inside the recovered picture to 0.

This is done for all filtered images; the ReLU layer improves a method's non-linear features. CNN's next step is to stack the layers, with the consequent of one layer serving as the input for the next layer. For "deep stacking," layers are repeated. The classification method is named after the last layer in the CNN structure, the FC layer. The middle layer and the FC layers are stacked together, with the middle layer voting on phantom "hidden" classes. Obviously, the extra layer allows the network to learn better feature integrations and come up with more effective solutions.Backpropagation (BP), which is processed by Deep Neural Networks, was used to obtain the measurements for the convolution layer and weights for the FC layers (DNN). For computing the modifications that exist in the system, BP in NN uses the mistake in the last solution.

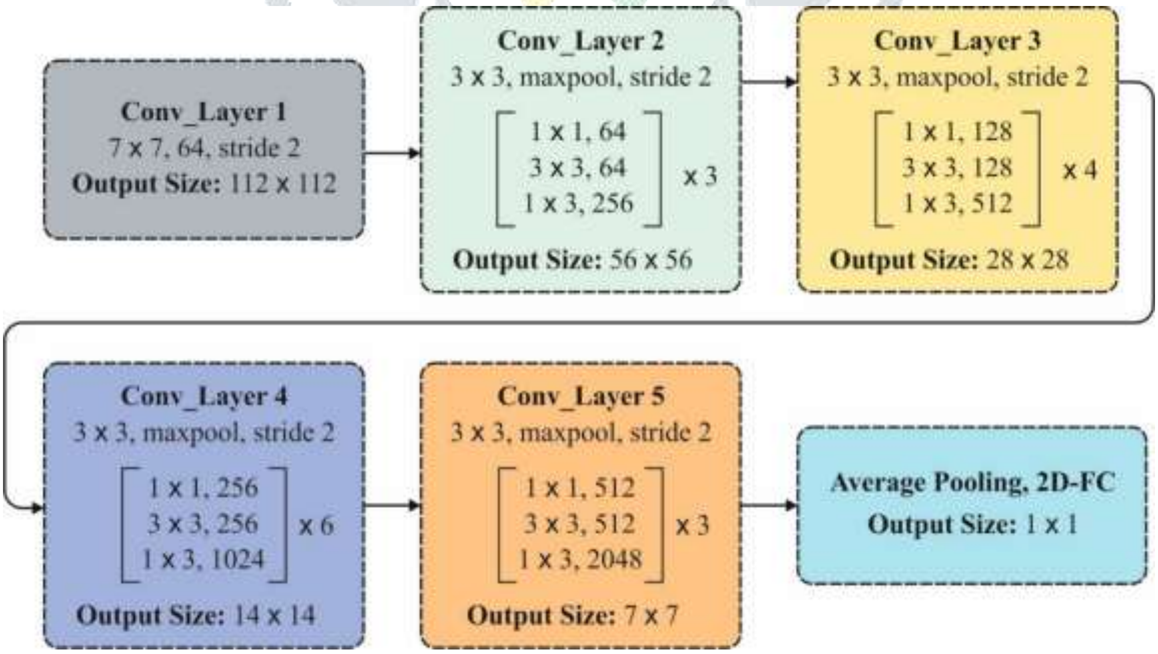


Fig. 2. Layered Structure of ResNet-50

The residual block is used by ResNet to overcome the decomposition and gradient disappearance concerns that are common in general CNNs. The residual block is not reliant on network depth, yet it improves a system's functionality. ResNet networks, in particular, have outperformed ImageNet in the classification process. The following is the function of the residual function:

$$y = F(x, W) + x \tag{1}$$

where x refers the input of residual block; W denotes the weight; y implies the result.The fundamental architecture of ResNet50 is depicted in Fig. 2.

2.4. Classification

Following the extraction of features from the ResNet-50 model, the classification process is carried out using the RF model, as outlined in the following sections.

2.4.1. RF model

RF is a well-known model classifier and regression model that has the capability of accurately identifying large datasets. An ensemble of DT is produced by the RF classifier. To construct a quick learner, ensemble methodologies are used to cluster vulnerable learners. The input is given at the top of the tree, and as it descends, the real data is tested at random, but by substituting the tiny data sets. The sample category is calculated using RF trees, from which the random number is obtained. The following steps are used to create an RF model:

– Step 1: Initialize N_{tree} bootstrap instances from actual data.

– Step 2: For the bootstrap instances, develop an un-pruned classification or regression tree.

– Step 3: For internal node, instead of selecting the optimal split between the predictors, which randomly selects m_{try} of M predictors and estimate the optimal split with the help of predictors.

– Step 4: Save tree along with the developed process.

– Step 5: Detect novel data by segmenting the predictions of N_{tree} trees. The prediction of RF is considered as trees for classification and for regression the maximum of predictions of all trees are showcased in Eq. (2):

$$S = \frac{1}{K}\sum_{K=1}^{K} K^{th} \tag{2}$$

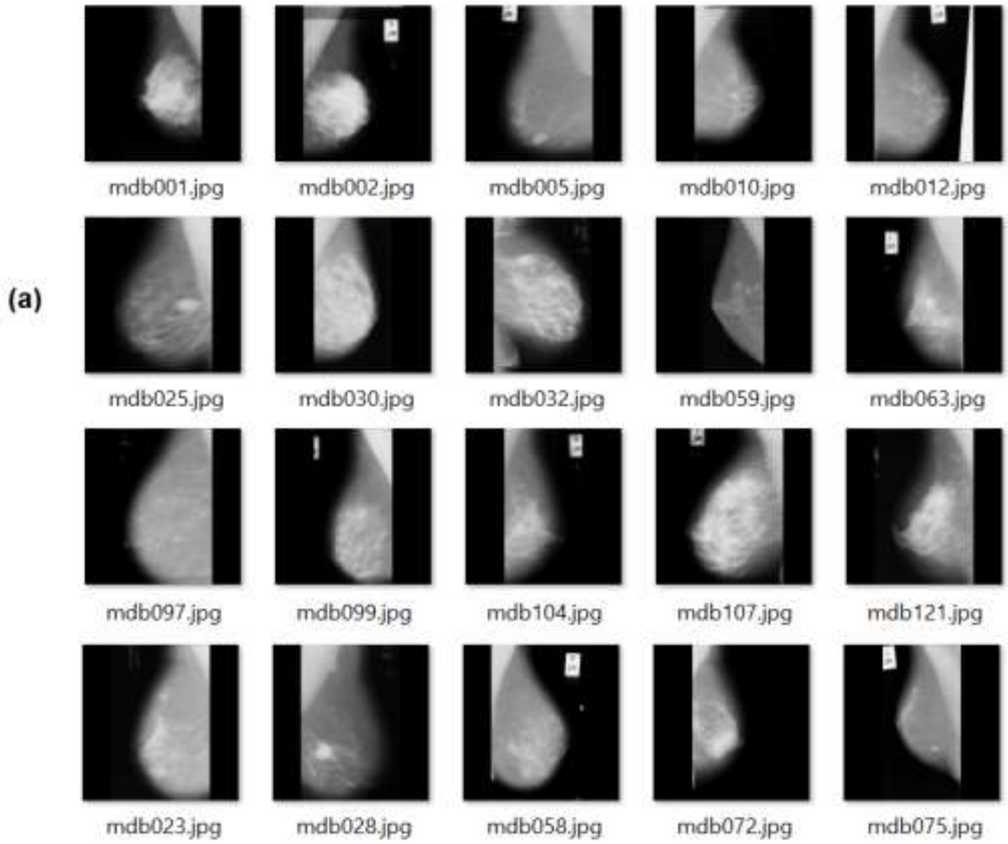
Where S implies of RF detection, K^{th} defines the tree response, and k refers the index runs across the individual trees.

3. Experimental Validation

The overall count of 322 mammography images from the Mini-MIAS dataset [13] was used to examine the final results of the DS-RN approach. It is made up of photos from three different class labels: benign, malignant, and normal. Table 1 provides information about a dataset, and Fig. 3 shows an example set of photographs.

Table 1 Dataset Description

Description	**Values**
Total Number of Images	322
Number of Classes	3
Number of Images in Normal Class	206
Number of Images in Benign Class	64
Number of Images in Malignant Class	52



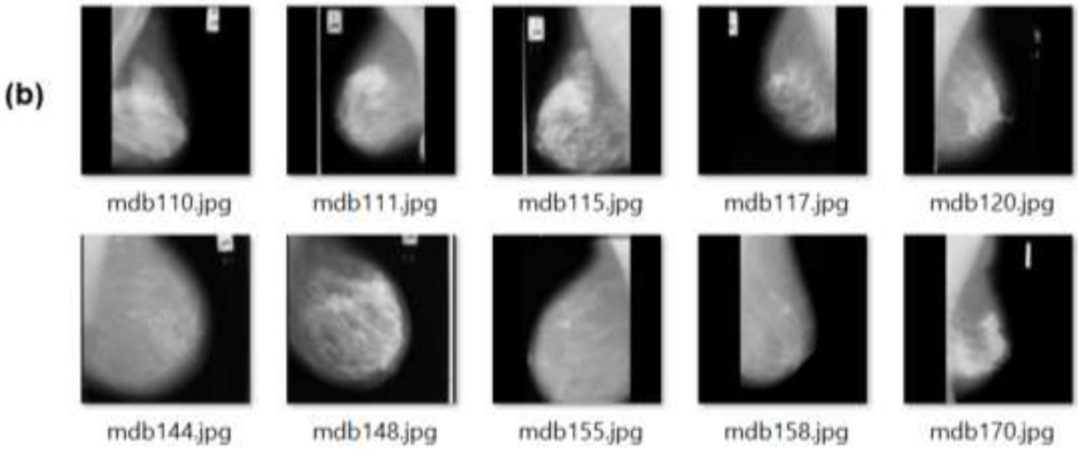


Fig. 3. Sample Images a) Benign b) Malignant

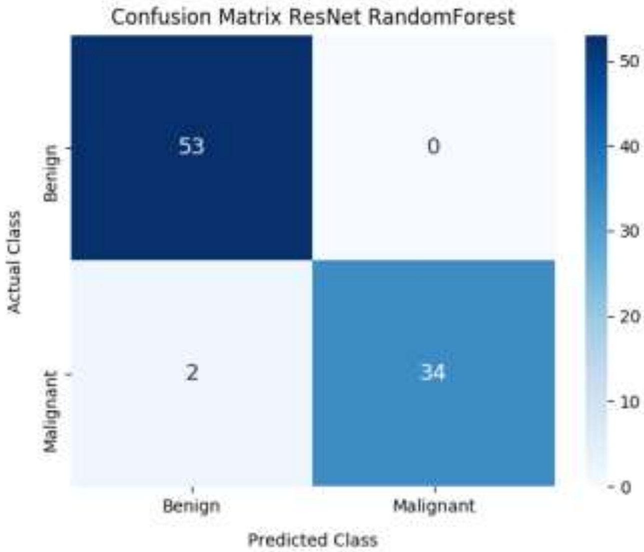


Fig.4. Confusion Matrix of Proposed DS-RNRF

On the classification of mammography images, the suggested DS-RNRF model generates a confusion matrix (Fig. 4). With 53 images classified as benign and 34 images classified as malignant, the RF classifier has achieved effective classification, as shown in the figure.

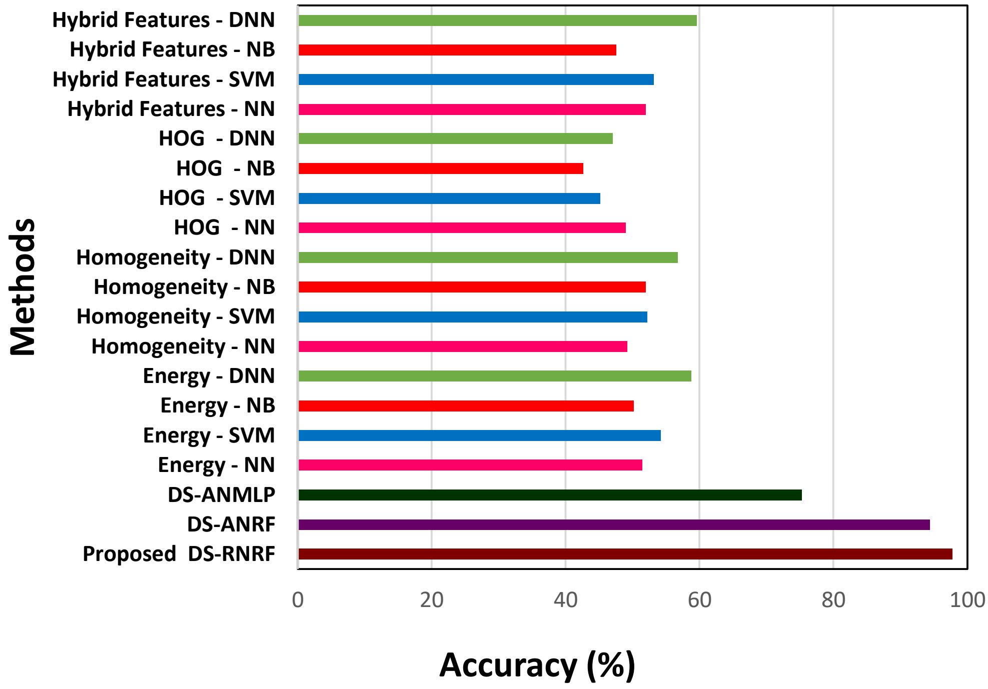


Fig. 5. Accuracy analysis of different methods

In Fig. 5, a complete comparison of the DS-RNRF classification result with previous approaches in terms of accuracy is shown. The HOG-NB technique has characterised poor classification results by achieving the lowest accuracy value of 42.6 percent, as seen in the figure. Similarly, with an accuracy score of 45.2 percent, the HOG-SVM technique is judged to have reasonable outcomes across the HOG-NB scheme. Furthermore, the HOG-DNN method has a 47 percent accuracy rating, which is acceptable. Following that, the Hybrid Features-NB, HOG-NN, Homogeneity-NN, and Energy-NB approaches surpassed earlier methods, achieving near-perfect accuracy values of 47.6%, 49.2%, and 50.2 percent, respectively. Furthermore, the Energy-NN framework has attempted to exhibit significant results by achieving a 51.4 percent accuracy.

Following that, the Homogeneity-NB and Hybrid Features-NN schemes both showed a 52 percent accuracy rating, which is similar and acceptable. Furthermore, the Homogeneity-SVM and Hybrid Features-SVM technologies produced accuracy values of 52.2 percent and 53.2 percent, respectively. Meanwhile, the Energy-SVM system has achieved maximum accuracy to the tune of 54.2 percent. Following that, the Homogeneity-DNN, Energy-DNN, and hybrid features-DNN techniques all produced superior results, with accuracy values of 56.8%, 58.8%, and 59.6%, respectively. Simultaneously, the DS-ANMLP and DS-ANRF techniques both produced qualified findings, with 75.28 percent and 94.38 percent accuracy, respectively. Furthermore, the newly proposed DS-RNRF technique has shown outstanding results, with the best accuracy of 97.75 percent.

4. Conclusion

The DS-RN model, a DL-based segmentation and classification model for breast cancer diagnosis utilising mammogram images, was created in this study. The input mammogram picture is first preprocessed before being segmented using the Faster RCNN model. Additionally, the ResNet model is used as a feature extraction model to find the most usable set of feature vectors from the segmented image. Finally, an RF model performs the categorization procedure. On the Mini-MIAS dataset, a detailed simulation process is completed to confirm the improved performance of the provided model. The DS-RN model achieved maximum classification performance with sensitivity, specificity, accuracy, and F-Measure of 96.36 percent, 100 percent, 97.75 percent, and 98.15 percent, respectively, according to the acquired experimental values.In the future, the proposed paradigm could be used to aid telemedicine in an IoT and cloud-based environment.

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