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Original Article

Kernel Piecewise Regressive Gradient Multilayer Perceptron Learning for Early Detection of Breast Cancer Using Mammographic Images

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Abstract *- Breast cancer is considered one of the most life-threatening forms of cancer among women worldwide. Early detection plays a pivotal role in helping doctors diagnose benign from malignant breast cancers for successful treatment and improved outcomes. Conventionally, breast cancer detection using machine learning and deep learning techniques has been developed for early diagnosis and treatment. However, achieving accurate detection with minimal time consumption poses significant challenges. A novel technique named Kernel Piecewise Regressive Gradient Multilayer Perceptron Learning (KPRGMPL) has been developed to address this Issue. It consists of three processes: preprocessing, feature extraction, and classification. The input layer receives numerous mammogram images. These images are processed through hidden layers. Image preprocessing in the first hidden layer is performed using Dixon's statistical Savitzky-Golay filtering technique by reducing noise artifacts. Radial kernel proximity lambda-connectedness image segmentation is performed in the second hidden layer to segment the image into multiple regions and extract the Region of Interest (ROI). Subsequently, features such as texture and size are extracted from the ROI for accurate cancer detection with minimal time. Finally, classification is carried out in the third hidden layer to detect breast cancer at an earlier stage by employing the Hamann indexive Piecewise Linear Regression(PLR). To minimize the error, a stochastic gradient function is applied. The accurately classified results are then obtained at the output layer. Experiments are evaluated with different evaluation metrics. The observed result shows the effectiveness of the proposed KPRGMPL technique, which has higher accuracy and minimum time than the existing methods.*

Keywords *- Breast Cancer Detection, Mammographic Images, Kernel Piecewise Regressive Gradient Multilayer Perceptron Learning, Dixon's Statistical Savitzky-Golay Filtering Technique, Radial Kernel Proximity Lambda-Connectedness Image Segmentation, Hamann Indexive Piecewise Linear Regression.*

1. Introduction

Cancer poses a significant public health challenge worldwide, carrying a high risk of mortality. Among women, breast cancer is the second most common type of cancer. Furthermore, its mortality rate is notably higher compared to other types of cancer. Breast cancer is a severe infection that affects women's breast cells. Early detection through screening and advancements in treatment have improved outcomes for many women diagnosed with breast cancer. Treatment options include surgery, chemotherapy, radiation therapy, and hormone therapy, based on the specific characteristics of the cancer and the patient's overall health. The utilization of imaging technologies, including Mammography, ultrasound, and Magnetic Resonance Imaging (MRI), has become the main approach for early detection of breast cancer. These technologies enable healthcare professionals to visualize and evaluate the breast tissue for abnormalities or signs of cancerous growth. Specifically, Mammography is widely used for routine screening in asymptomatic individuals for further evaluation of suspicious findings and the early identification and diagnosis of breast cancer. This helps to facilitate timely treatment to improve the patient's health conditions and minimize the mortality rate. Several machine learning techniques have been developed for breast cancer detection.

A hybrid structure, which includes a Convolutional Neural Network (CNN) and Bidirectional Long Short-Term Memory (BiLSTM), was developed in [1] to enhance the accuracy of breast cancer classification. However, it faced challenges in accurately identifying breast cancer within a minimal time when applied to a large volume of mammogram image datasets. A unique method termed BreastNet-SVM was developed in [2] with the aim of identifying breast cancer from mammograms through precise segmentation and classification of breast tissues. However, it faced challenges in adopting different sizes of mammography images in breast cancer detection.

A new metaheuristic algorithm-based machine learning approach was introduced in [3], which utilizes Fuzzy C Means segmentation for detecting breast cancer from mammogram images. However, enhancing precision in breast cancer detection remains a challenging issue. A new computer-aided diagnosis approach was developed in [4] for breast cancer classification, utilizing an integration of deep neural networks and transfer learning. However, it failed to handle more complex datasets to diagnose breast cancer images with higher accuracy.

Machine learning and deep learning methods were developed in [5] for breast cancer detection. However, it failed to produce a more efficient classification system for detecting normal, benign, and cancerous conditions. CNN classifiers were developed in [6] to identify breast cancer by categorizing mammogram images into benign, cancerous, or normal classes. However, it did not observe and evaluate the performance of the classifiers to improve the accuracy of the results. A novel two-stage deep learning method was developed in [7] with the aim of detecting breast cancer. However, the designed method has a few misclassified results in breast cancer detection.

Numerous deep CNN methodologies were developed in [8] for diagnosing breast cancer. However, it faced challenges in accurately localizing and segmenting breast tissue to improve disease identification. A Transferable Texture Convolutional Neural Network (TTCNN) was introduced in [9] to enhance the accuracy of breast cancer detection and classification through the extraction of texture features. However, the time complexity of breast cancer detection was not reduced. Deep learning techniques for breast mammogram classification were developed in [10]. However, the time complexity of breast mammogram classification was high.

The Mask R-CNN method was introduced in [11] with the aim of achieving higher performance of breast cancer detection. However, the accuracy of breast cancer detection did not improve when larger image datasets were considered. A cascade deep learning network was developed in [12] to enhance breast cancer detection through classification. However, it failed to enhance performance in classifying breast cancer with more complex features.

Machine learning and deep learning approaches were introduced in [13] for screening and early detection of breast cancer. An automatic breast mass segmentation and classification system was developed in [14] with the aim of achieving classification accuracy for distinguishing between benign and suspicious masses. A multi-task deep GCN method was designed in [15] for the automatic classification of breast cancer detection using mammograms. Table 1 shows the comparison table for existing methods.

Table 1. Comparison table for existing methods

S. No	Methods	Merits	Demerits
1	CNN and BiLSTM	Enhance the accuracy of breast cancer classification	Failed to identify breast cancer within a minimal time
2	BreastNet-SVM	Sensitivity and specificity were improved by the designed SVM method	Failed to adopt different sizes of mammography images in breast cancer recognition
3	Metaheuristic algorithm-based ML approach	Computational time was reduced	Precision was not improved in breast cancer detection
4	New computer-aided diagnosis approach	Accuracy was improved	Failed to manage a more complex database to diagnose breast cancer images
5	ML and DL methods	Breast cancer recognition using improved accuracy and specificity	Failed to produce a more efficient classification system
6	CNN classifiers	Improve the accuracy of classification results.	Failed to examine and estimate the performance of the classifiers to enhance the accuracy outcomes
7	Two-stage DL method	Object recognition model using enhanced classification accuracy	It has a few misclassified results in breast cancer detection
8	Numerous deep CNN methodologies	Improve the accuracy of classification performance and score	The CNN method was not accurately localizing and segmenting breast tissue for improving disease identification
9	TTCNN	Improve the accuracy of breast cancer detection and classification	The time complexity of breast cancer detection was not reduced
10	Mask R-CNN method	Achieving higher performance in breast cancer recognition	The accuracy of breast cancer recognition did not improve

1.1. Research Gap

Breast Cancer is a common cancer in women and is the second leading cause of death worldwide. Several ML and DL approaches were developed for breast cancer detection using mammogram images. However, the conventional DL method focused on limited mammogram images for cancer discovery. Also, accurate and timely detection faces major challenges. Also, the precision and recall are unable to concentrate on cancer detection. To address this Issue, the proposed KPRGMPL technique is introduced for the accurate and timely prediction of breast cancer using mammogram images. This technique is employed for clinical practice by enabling faster diagnosis, targeted treatment, and better preventative strategies. Dixon's statistical Savitzky-Golay filtering technique is utilized to reduce the noise and enhance the PSNR.

Also, the radial kernel proximity lambda-connectedness image segmentation is employed to extract ROI and texture features to reduce the time. Finally, the Hamann Indexive Piecewise Linear Regression is used to accurately detect breast cancer and enhance precision.

1.2. Novelty and Contributions

- The proposed KPRGMPL technique is introduced to improve breast cancer detection accuracy. It integrates distinct processes, including preprocessing, segmentation, feature extraction, and classification, into the Multilayer Perceptron Learning network.
- Dixon's statistical Savitzky-Golay filtering technique is utilized in the proposed KPRGMPL technique to execute preprocessing for noise removal and image quality enhancement. The KPRGMPL technique uses Dixon's statistical test in a $k * k$ filtering window concept for preprocessing. Also, the Savitzky-Golay is employed to estimate the coefficients of the polynomial. Hence, it reduces the time spent forecasting air pollution.
- Radial Kernel Proximity Lambda-Connectedness Image Segmentation uses the KPRGMPL technique to extract the Region Of Interest (ROI). The similarity between the pixels is evaluated by using a radial kernel function. Then, the ROI images are segmented via lambda. With this, the time required for breast cancer detection is said to be reduced.
- Feature extraction is carried out using the KPRGMPL technique to extract the texture features while minimizing the time.
- Hamann Indexive Piecewise Linear Regression is utilized in the KPRGMPL technique to execute classification. The Hamann similarity index is used to examine the extracted features and ground truth features. Piecewise Linear Regression is employed to detect breast cancer. This improves the accuracy of breast cancer detection.
- Stochastic gradient descent is applied to update the weights to minimize error in breast cancer detection for precise breast cancer detection.

1.3. Outline of Paper

The remainder of this paper is organized as follows: Section 2 discusses Related Works, reviewing the existing literature on breast cancer detection and classification. Section 3 provides an explanation of the proposed KPRGMPL technique, with a neat architecture diagram illustrating the different processes. Section 4 describes the simulation setup, including details about the dataset used for evaluation. Section 5 discusses the performance outcomes obtained from the implementation of the KPRGMPL technique, comparing them with the results of existing methods. Section 6 presents the discussion, and Section 7 summarizes the conclusions.

2. Related Works

An efficient transfer and ensemble learning method was developed in [16] for breast abnormality diagnosis with better accuracy. However, the method failed to provide a more robust model. A new constraint-based algorithm was designed in [17] to categorize a mammogram image as cancerous with fewer false positives. However, the time complexity performance for abnormality diagnosis did not improve.

Multiple pre-trained Convolutional Neural Network (CNN) models were developed in [18] with the aim of detecting breast cancer through feature extraction and reduction. However, it failed to enhance the accuracy and predictive capabilities. A novel automated computerized approach was introduced in [19] for breast cancer classification. However, the designed approach consumed more time for breast cancer classification. A novel approach was designed in [20] to automate the evaluation of abnormalities using mammograms for breast cancer identification.

A deep learning technique was introduced in [21] for identifying breast cancers using mammogram images from multi-institutional datasets. However, validation with a huge sample size was not conducted, limiting the ability to perform further experiments. Two deep learning methods, namely AlexNet and ResNet-18, were introduced in [22] for breast tumor detection. However, the execution time performance was not minimized as these methods failed to automatically extract the Region Of Interest (ROI). A Deep Convolutional Neural Network (CNN) model was developed in [23] for the automated detection of breast cancer using mammogram images with different classes. However, it failed to enhance the performance of the object detection network.

A novel Deep Convolutional Neural Network (DCNN) was introduced in [24] based on feature combination and an ensemble learning technique to improve the detection and classification of abnormalities in mammographic scans. However, the robustness of the model was not enhanced. A Convolutional Neural Network (CNN) classifier was developed in [25] for detecting breast cancer utilizing Mammographic Image Analysis. Nevertheless, it failed to produce high performance and fast results for early diagnosis. The integration of Deep Learning and Handcrafted Features for the detection of Benign and Malignant Breast Tumors was introduced in [26]. However, the designed method was found to be ineffective when applied to other medical images for Breast Tumor detection.

An automatic segmentation method was presented in [27] for breast cancer detection. But the deep learning model was not applied to improve breast cancer detection results. A deep feature transfer learning model was developed in [28] for the classification of breast tumors. However, it did not perform experiments using mammogram images for breast tumor detection.

A hybrid CNN-LSTM model was introduced in [29] for breast histopathological image classification. Eight pre-trained CNN models were introduced in [30] based on transfer learning to observe the classification performance of breast cancer. However, different contrast and illumination techniques were not explored to enhance image quality. Advanced data analytics were employed in [31] for early and accurate Breast Cancer Diagnosis. But the precision was not increased. A sophisticated Computer-Aided Detection (CAD) framework was discussed in [32] to ensure diagnostic efficiency. However, the accuracy was not sufficient. An efficient federated learning method was introduced in [33] to detect breast cancer without compromising time. To address this Issue, a Deep learning-based method was examined in [34] employing a CNN for early detection. Early diagnosis is crucial for minimizing the mortality rate in those with breast cancer. An intelligent integrated diagnosis method was developed in [35] with a CNN and Bayesian networks to achieve good diagnostic accuracy. But the time was higher.

3. Proposal Methodology

Breast cancer occurs due to abnormal cell growth among women worldwide. These cells are classified as either cancerous or noncancerous based on their location, size, and characteristics. The initial stage of cancerous cell development is referred to as benign, while the more advanced stage is known as malignant, characterized by rapid spread to different body organs. Early detection and diagnosis are crucial for preventing high mortality rates. A precise and efficient diagnostic method is required for medical professionals to distinguish between benign and malignant breast cancers before undergoing surgical procedures. This section introduces a novel KPRGMPL technique for accurate Breast Cancer Detection with minimal time consumption. The process of the KPRGMPL technique is depicted in Figure 1.

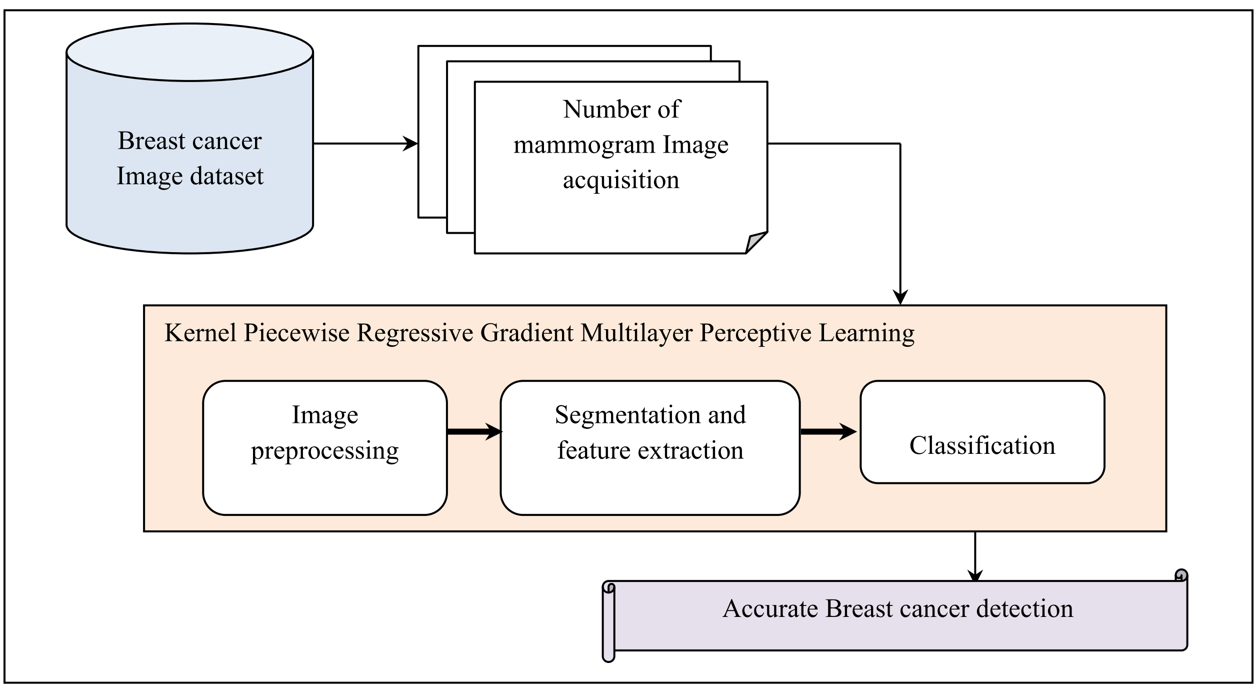

Fig. 1 Architecture of the proposed KPRGMPL technique

Figure 1 above illustrates the architecture diagram of the proposed KPRGMPL technique for the accurate detection of breast cancer. The accurate detection method involves four fundamental steps: image acquisition, preprocessing, segmentation, feature extraction, and classification. Initially, the breast cancer image dataset is considered. The number of mammogram images is collected from the dataset during image acquisition. Next, image preprocessing removes noisy pixels using Dixon's statistical Savitzky-Golay filtering technique. Subsequently, the segmentation and feature extraction process is performed using radial kernel proximity lambda-connectedness image segmentation to extract RoI and texture features. Finally, the proposed KPRGMPL technique utilizes Hamann indexive piecewise linear regression to classify breast cancer to achieve higher accuracy and minimize errors. These fundamental processes of the proposed KPRGMPL technique are explained briefly in the following subsections.

3.1. Image Acquisition

Image acquisition is the fundamental step in the image processing technique. It is the process of collecting the numerous Mammographic Images from the CBIS-DDSM: Breast Cancer Image Dataset. The CBIS-DDSM dataset is a widely used dataset in the field of breast cancer detection. It contains digital mammograms, which are breast X-ray images, along with associated metadata such as patient information, lesion information, and imaging parameters.

3.2. Kernel Piecewise Regressive Gradient Multilayer Perceptron Learning

A Multilayer Perceptive Learning is a type of Deep Learning Artificial Neural Network with multiple layers of nodes (i.e., neurons) organized into an input layer, one or more hidden layers, and an output layer. Multilayer Perceptron Learning is a feed-forward Neural Network, and the information flows in one direction, from the input to the output layer through the hidden layer.

Multilayer Perceptron Learning consists of multiple layers of nodes, including an input layer, one or more hidden layers, and an output layer. Each layer, except the input layer, contains multiple neurons to transfer the input from one layer to another. The structure of the proposed Multilayer Perceptron Learning network is shown in Figure 2.

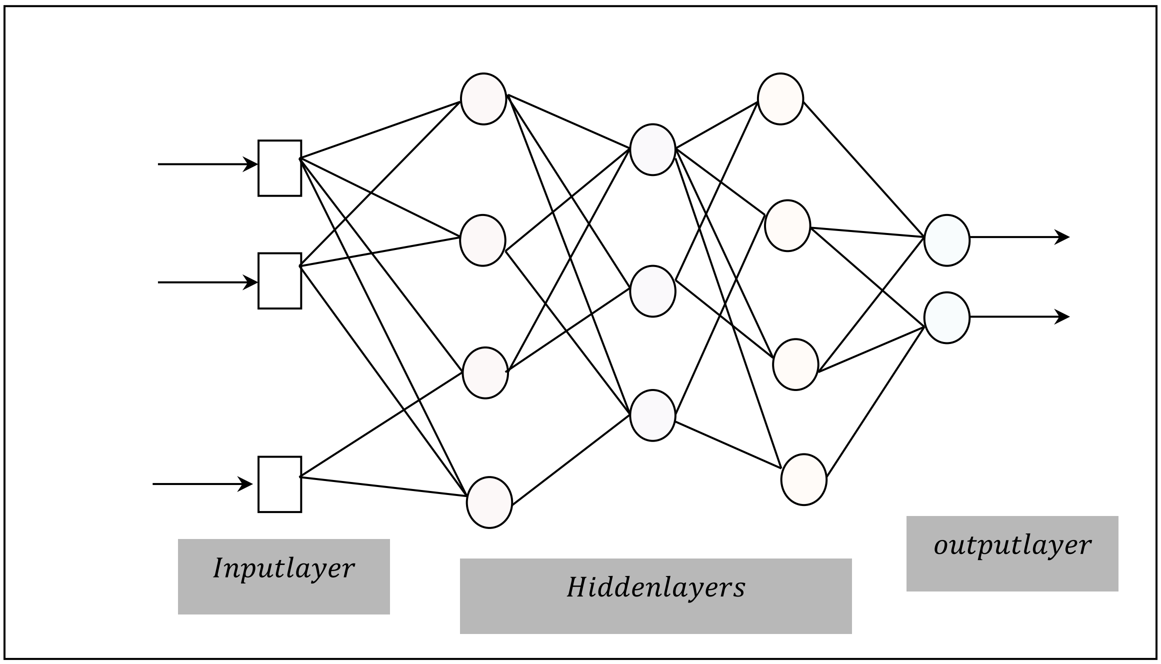

Fig. 2 Construction of a multilayer perceptron learning network

Figure 2 depicts the construction of a Multilayer Perceptron learning network, which includes three main layers: input, hidden (i.e., middle), and output layers. The input and output layers are always single layers, whereas the middle layer includes multiple sublayers for processing the given input. Each layer consists of small individual units called Artificial Neurons, Perceptrons, or Nodes.First, the input layer receives the number of mammogram images. $MI_1, MI_2, MI_3 \dots MI_n$. The weight and bias are assigned for each image in Equation (1).

$$A = [\sum_{i=1}^{n} MI_i * w_i] + Z \tag{1}$$

Where, A indicates an activity of a neuron,'w_i'denotes a weight, MI_i Indicates a number of mammogram images and adds to the bias function 'Z' that stores the numerical value of '1'. Then the input is forwarded into the first hidden layer. The mammogram images are then processed through the hidden layers for computation.

3.3. Dixon's Statistical Savitzky-Golay Filtering Technique-based Image Preprocessing

The first step of the proposed KPRGMPL technique is the image preprocessing, which refers to a process of enhancing the quality of the images by removing the noise. The proposed technique utilizes Dixon's statistical Savitzky-Golay filtering technique for noise removal and increasing the image quality. This filtering technique is used to smooth the input mammogram images through noise reduction. Let us consider the input image and mammogram images. $MI_1, MI_2, MI_3 \dots MI_n$. The number of pixels in each image is represented as $Q_1, Q_2, Q_3 \dots Q_m$. The proposed technique selects a window size of $k * k$. Then the pixels are arranged into the filtering window,

Q_1	Q_2	Q_3
Q_4	Q_5	Q_6
Q_7	Q_8	Q_9

Fig. 3 k * k filtering window

Figure 3, given above, illustrates the $k * k$ filtering windows where the pixels. $Q_1, Q_2, Q_3 \dots Q_m$ They are arranged in rows and columns. After that, the pixels are rearranged in increasing order.

After that, the absolute difference between the pixels and the neighboring pixels is determined using Equation (2).

$$D = \frac{|Q_j - Q_{jnn}|}{Q_l - Q_f} \quad (2)$$

Where D denotes a Dixon's statistical outcome, Q_f indicates a first pixel in the increasing order, Q_l denotes the last pixel in the increasing order, Q_j denotes a current pixel and Q_{jnn} Indicates a neighboring pixel in the filtering window. The Dixon's statistical test provides outcomes ranging from 0 to 1. When the value of Dixon's statistical test is lower, the pixels are considered normal. Otherwise, the pixels are identified as noisy and are smoothed by applying the polynomial with 'd' degrees. Then fit a polynomial coefficient by a linear set of 'm'pixels as given below Equation (3),

$$Z = C_0 + C_1 Q_1 + C_2 {Q_2}^2 + C_3 {Q_3}^3 \dots . + C_n {Q_m}^d \quad (3)$$

Where Z indicates a polynomial function, $C_0, C_1 \dots C_m$ denotes a polynomial coefficient, Q_m Represents a pixel in the filtering window. As a result, the noisy pixels are replaced with smoothed values based on a polynomial function. In this way, image preprocessing is performed to enhance the image quality.

3.4. Radial Kernel Proximity Lambda-Connectedness Image Segmentation

After the image preprocessing, the segmentation process is performed in the second hidden layer to extract the ROI and other features from the image. This process helps to minimize the time spent on Breast Cancer Detection. Segmentation in Breast Cancer Detection refers to the process of partitioning an image into multiple segments or regions based on characteristics of pixel intensity.

The proposed KPRGMPL technique utilizes the Radial Kernel Proximity Lambda-Connectedness method to segment the image into different regions based on connecting pixels with similar pixel intensity in the image.

Let us consider the Graph theory, $g = (Q_i, R)$ where, Q_i denotes a pixel $Q_{1,} Q_2, Q_3, \dots Q_m$ And 'R' denotes a pixel connectivity or connectedness. The proposed method segments the Region based on the connectivity between the pixel values within a certain range defined by a parameter λ (λ).

The Radial Kernel Function is applied to measure the similarity between the pixels as given below in Equation (4),

$$K = \exp\left(-\frac{1}{2\,\sigma^2} |Q_i - Q_{i+1}|^2\right) \quad (4)$$

Where 'K 'is the Radial Kernel Function, $|Q_i - Q_{i+1}|$ indicates the difference between the two pixel intensities Q_i and Q_j, 'σ' represents a deviation parameter σ>0. The output of the Radial Kernel Function provides a value between 0 and 1.

Therefore, the degree of connectivity between the pixel intensities is estimated by applying the graph segmentation algorithm as given below in Equation (5),

$$R = max\{K\left(Q_{i,} Q_{i+1} \middle| i = 1,2, \dots m\right)\} \quad (5)$$

Where 'R' denotes a connectivity or connectedness between the pixel intensity $Q_{i,}$ and Q_{i+1}, K denotes a kernel function output ranging from 0 to 1. Then define the value for the lambda parameter (λ), i.e., 0.5, which determines the range of intensity values over which pixels are considered Lambda-Connected in Equation (6).

$$Y = \begin{cases} K > \lambda, \ connected \\ otherwise, \ not - connected \end{cases} \quad (6)$$

From the above (6), a kernel value greater than the lambda parameter (λ), i.e., 0.5, indicates that the adjacent pixels are connected to form a region. In this way, image segmentation is performed to extract the ROI and minimize the time consumption of breast cancer detection.

Following this, geometric features such as area, perimeter, and texture are extracted from the ROI image. The formula calculates the area of the ROI by summing up the areas of all pixels within the ROI, as given below in Equation (7),

$$a_{ROI} = \sum_i \sum_j a_{ij} \quad (7)$$

Where, a_{ROI} Denotes an area of the ROI, a_{ij} Denoting an area of all pixels within the ROI. The perimeter of the segmented ROI is measured by counting the number of boundary pixels. It is the length of the extracted ROI boundary. The perimeter is formulated in Equation (8),

$$p_{ROI} = \sum_i \sum_j p_{ij} \quad (8)$$

Where, p_{ROI} denotes a perimeter, p_{ij} Denotes a number of boundary pixels.

The texture feature is used for extracting the spatial patterns or structures in the image based on the correlation of pixel intensity with mean and standard deviation, according to Equation (9).

$$Tx = \sum_i \sum_j \frac{1}{d^2}\left[(Q_i - \mu_i)(Q_j - \mu_j)\right] \quad (9)$$

Where Tx denotes a texture correlation between the pixel Q_i and its neighboring pixels Q_j based on the mean μ_i and μ_j And the deviation' d'.

These extracted features are given to the third hidden layer, where the cancer detection is performed.

3.5. Hamann Indexive Piecewise Linear Regression-Based Breast Cancer Detection

Finally, the proposed KPRGMPL technique performs the classification in the third hidden layer for Breast Cancer Detection with the extracted features. In that layer, the Hamann Indexive Piecewise Linear Regression is applied to analyze the extracted features and the testing features. It is a Machine Learning Technique used for analyzing the extracted features and the ground truth features based on the Hamann Index Function. It is a statistical technique used for estimating the two features as given below in Equation (10),

$$HI = 1 - \frac{2|\, F_E \,\Delta\, F_T|}{n} \quad (10)$$

Where, HI denotes a Hamann Index Function, F_E denotes extracted features, F_T Denotes a ground truth feature, 'n denotes a data sample size, $F_E \,\Delta\, F_T$ Denotes a variation between the features. The test' HI' returns a value from 0 (no correlation between the two features) to 1 (complete correlation between the two features). The Piecewise Linear Regression is used to categorize the image into different parts, i.e., normal, benign, and malignant cases. The similarity value is transferred into the output layer, where the sigmoid step activation function is applied to provide the final classification results in Equation (11).

$$Y = A(h_3 * w_{ho} \quad (11)$$

Where Y denotes an output of classification, A denotes a sigmoid activation, h_3 denotes an output of the previous hidden layer, w_{ho} denotes a weight between the hidden and output layer. For each outcome, the error rate 'E' is computed based on the squared difference between the actual outcome and the output predicted in Equation (12).

$$E = (Y_a - Y)^2 \quad (12)$$

In order to minimize the error, the stochastic gradient is applied to adjust the weight in Equation (13).

$$w_{(t+1)} = w - \eta \left[\frac{\partial E}{\partial w}\right] \quad (13)$$

Where,$w_{(t+1)}$ adjusted weight, w indicates a current weight, η denotes a learning rate, $\left[\frac{\partial E}{\partial w}\right]$ The gradient function is the first-order derivative algorithm with respect to the error and weight. Finally, the accurate cancer detection results are obtained at the output layer with minimum error. The algorithmic process of the proposed technique is described as follows. The Kernel Piecewise Regressive Gradient Multilayer Perceptron Learning algorithm is described as given below,

//Algorithm 1: Kernel Piecewise Regressive Gradient Multilayer Perceptron Learning
Input: Dataset, Number of mammogram images$MI_1, MI_2, MI_3 \ldots MI_n$. Output: Increase the breast cancer detection accuracy
Begin Step 1: Number of mammogram images $MI_1, MI_2, MI_3 \ldots MI_n$ taken in the input layer Step 2: For each image MI Step 3: Assign the weight'w_j'and bias' v' in first hidden layer Step 4; end for Step 5: Arrange the pixels$Q_0, Q_1, Q_2, \ldots \ldots Q_m$ in widow Step 6: Measure the Dixon's statistical test Step 7: Find noisy pixels using (2) Step 8: Replace noisy pixels using (3) Step 9: Return (preprocessed image) Step 10: For each preprocessed image-- second hidden layer Step 11: Measure the radial kernel function between pixels using (4) Step 12: if $(K > \lambda)$ then Step 13: Neighboring pixels are connected Step 14: else Step 15: Neighboring pixels are not connected Step 16: end if

Step 17: Segment the connected pixels
Step 18: Extract ROI
Step 19: Extract area, perimeter, and texture features using (7) (8) (9)
Step 20: End for
Step 21: For each extracted feature -- third hidden layer
Step 22: Measure the Hamann index function using (11)
Step 23: $if\ (HI = 1\ )$ then
Step 24: The Image is accurately classified either as normal, benign, or malignant
Step 25: end if
Step 26: For each classification result
Step 27: Measure the error rate' E'
Step 28: Apply the Stochastic gradient to adjust the weight'$w_{(t+1)}$'
Step 29: Obtain final classification results with minimal error at the output layer
Step 30: End for
End

Algorithm 1 describes a step-by-step process for breast cancer detection with higher accuracy and minimal time consumption. Mammogram images are provided as input to the deep learning classifier. The input is then transferred into the first hidden layer, where a set of weights and biases is applied. In this layer, Dixon's statistical Savitzky-Golay filtering technique is used to remove noise from the mammogram image and enhance its quality. The Radial Kernel Proximity Lambda-Connectedness image segmentation process is executed to extract the Region Of Interest (ROI) from the image and extract shape features such as area, perimeter, and texture features. These extracted features are then passed to the third hidden layer, where the Hamann Index function is applied to analyze the extracted features with ground truth features. Based on this feature analysis, it accurately classifies images as normal or abnormal. Subsequently, the error is calculated for each predicted output. The stochastic gradient is then applied to update the weights and to minimize the error. Finally, accurate breast cancer detection with minimal error is achieved at the output layer.

4. Experimental Scenario

In this section, experimental evaluation of the proposed KPRGMPL and existing CNN-BiLSTM [1] and BreastNet-SVM model [2] is carried out using MATLAB simulator using CBIS-DDSM: Breast Cancer Image Dataset.

4.1. Dataset Description

The Curated Breast Imaging Subset of DDSM CBIS-DDSM) is an enhanced and standardized iteration of the Digital Database for Screening Mammography (DDSM). The Breast Cancer Image Dataset was extracted from https://www.kaggle.com/datasets/awsaf49/cbis-ddsm-breast-cancer-image-dataset. The DDSM comprises 2,620 scanned film mammography studies, including normal, benign, and malignant cases with verified pathology information. The extensive scale of this database, integrated with its validated ground truth, makes the DDSM a useful tool in breast cancer detection and diagnosis. The dataset includes 10239 mammogram images for cancer detection.

For the experimental consideration, the number of images taken ranges from 500 to 5000. The external validation is determined to measure the performance of the model's ability to carry out hidden data. By using this validation, the database is separated into training and testing. Most data samples (80%) were employed for training, and the remaining (20%) were taken for testing. The 10-fold cross-validation is used for measuring results. The dataset size is 6.3 GB. The images were decompressed and converted to a DICOM format. Table 2 describes the dataset description, and Table 3 shows the hyperparameters and their description employed in the proposed method.

Table 2. CBIS-DDSM dataset description

S. No	Features	Values
1	Number of Studies / Series	6775
2	Number of Participants	1566
3	Number of images	10239
4	Modalities	MG
5	Image size (GB)	6

Table 3. Hyperparameters and Description

S. No	Hyperparameters	Description
1	Number of layers used	Five layers (one input, three hidden, and one output)

2	Activation function used in hidden layers	Dixon's statistical Savitzky-Golay filtering technique is used in the first hidden layer. Radial Kernel Proximity Lambda-Connectedness method is used in the second hidden layer, and Hamann Indexive Piecewise Linear Regression is employed in the third hidden layer.
3	Activation function used in the output layer	Stochastic gradient function
4	Learning rate	The value of the learning rate is 0.01.
6	Batch size	A batch size of 64 is considered for simulation.
7	Number of epochs	The number of epochs is 10

5. Performance Results and Analysis

In this section, the performance of KPRGMPL and existing CNN-BiLSTM [1] and BreastNet-SVM model [2] is analyzed with different performance metrics such as peak signal-to-noise ratio, breast cancer detection accuracy, precision, and breast cancer detection time. The performances of proposed and existing methods are discussed with the help of a table and a graphical representation.

5.1. Performance Analysis of the Peak Signal-to-Noise Ratio

It is used to evaluate the quality of a reconstructed image by comparing it to the original image and measuring the ratio of the peak signal power to the noise power. It is expressed in Decibels (dB). PSNR is calculated using the Mean Squared Error (MSE) between the original and preprocessed image. The formula for PSNR is given below in Equations (14) and (15),

$$PSNR = 10 * \log_{10}\left[\frac{MQ^2}{MSE}\right] \tag{14}$$

$$MSE = [Original_{size} - PP_{size}]^2 \tag{15}$$

Where '$PSNR$' indicates a peak signal to noise ratio,'MQ^2'represents the maximum possible pixel value (255), MSE indicates a mean square error, PP_{size} indicates preprocessed image size, $Original_{size}$ Denotes original image size. Table 4 shows the PSNR of the proposed KPRGMPL and existing CNN-BiLSTM [1] and BreastNet-SVM model [2].

Table 4. Comparative evaluation of peak signal to noise ratio using proposed KPRGMPL and existing CNN-BiLSTM [1] and BreastNet-SVM model [2]

Image Size (MB)	Peak Signal to Noise Ratio (dB)		
	KPRGMPL	CNN-BiLSTM	BreastNet-SVM model
1.23	69.04	64.04	61.68
1.39	67.30	64.60	59.18
1.56	68.13	65.20	62.33
1.70	71.22	66.54	59.18
1.44	70.06	67.30	64.04
1.16	66.54	59.83	58.30
1.71	69.54	66.19	63.12
2.25	68.48	65.85	62.11
2.50	70.40	66.12	62.55
2.85	63.80	60.61	56.65

Figure 4 portrays the performance analysis of Peak Signal-to-Noise Ratio (PSNR) versus different sizes of input mammogram images, measured in MEGABYTES (MB). Three methods were employed to measure PSNR: KPRGMPL, the existing CNN-BiLSTM [1], and the BreastNet-SVM model [2]. Among these three methods, the KPRGMPL technique exhibited better PSNR performance. Let us consider the $1.23MB$ size of a Mammogram Image for computing the PSNR. By applying the KPRGMPL technique, the PSNR performance was observed to be 69.04dB. Likewise, the PSNR performances were observed to be 64.04dB and 61.68dB when applying methods [1] and [2], respectively. Similarly, different performance outcomes were observed for different sizes of images. The overall performance of the KPRGMPL technique is compared to that of existing methods. The comparison results show that the PSNR performance using the KPRGMPL technique improved by 6% compared to the existing method [1] and by 12% compared to method [2], respectively.

This improvement is achieved by applying Dixon's statistical Savitzky-Golay filtering technique in the KPRGMPL to enhance image quality by removing noise artifacts. Dixon's statistical test is utilized to measure the deviation between pixels in the filtering window. Then, noisy pixels are replaced with the polynomial degree of other pixels in an image, thereby minimizing the mean square error and increasing the peak signal-to-noise ratio.

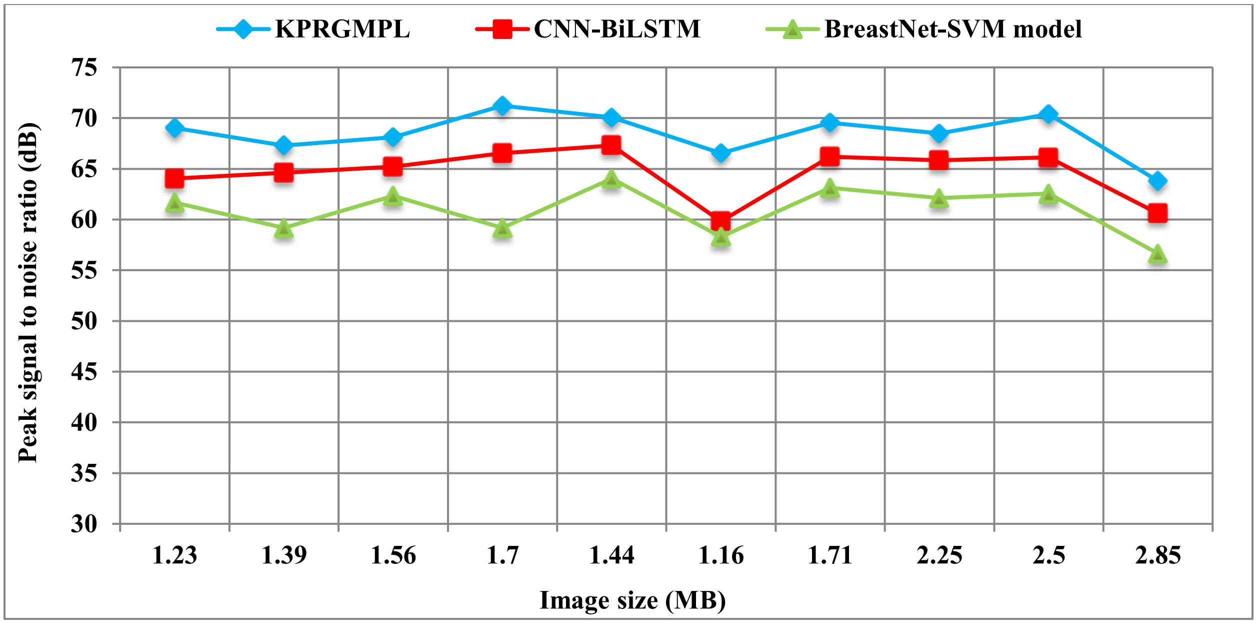

Fig. 4 Graphical illustration of peak signal-to-noise ratio versus image size

5.2. Performance Analysis of Breast Cancer Detection Accuracy

It is measured as the ratio of the number of breast images that are correctly classified as normal, benign, and malignant from the total number of input images. The accuracy is formulated as given below in Equation (16),

$$BCDA = \left(\frac{TRP+TRN}{TRP+TRN+FLP+FLN}\right) * 100 \qquad (16)$$

Where, $BCDA$ indicates Breast Cancer Detection Accuracy, TRP denotes the True Positives, TRN denotes a True Negative, FLP denotes a False Positive, FLN indicates a False Negative. The accuracy is measured in percentage (%).

The result of BCDA is estimated in Table 5 for the proposed KPRGMPL and existing CNN-BiLSTM [1] and BreastNet-SVM model [2] methods.

Table 5. Comparative evaluation of breast cancer detection accuracy using the proposed KPRGMPL and the existing CNN-BiLSTM [1] and BreastNet-SVM model [2]

Number of Mammogram Images	Breast Cancer Detection Accuracy (%)		
	KPRGMPL	CNN-BiLSTM	BreastNet-SVM Model
500	90	86	84
1000	89.65	85.65	83.62
1500	91.22	88.42	85.52
2000	90.86	87.2	85.78
2500	91.96	85.63	83.65
3000	92.45	88.74	86.41
3500	91.2	87.98	85.56
4000	90.56	89.56	87.47
4500	91.75	88.35	86.45
5000	90.78	87.45	85.96

The above Table 5 and Figure 5 illustrate the graphical representation of Breast Cancer Detection accuracy using three different methods, namely KPRGMPL, the existing [1], and the [2]. The results indicate an improvement in Breast Cancer Detection accuracy when employing the KPRGMPL technique compared to other existing methods. Considering 500 mammogram images, the Breast Cancer Detection accuracy was found to be 90% using the KPRGMPL technique, while [1, 2] achieved 86% and 84% accuracy, respectively. Ten different results were observed for each method with varying numbers of images. Finally, averaging the ten comparison results shows that breast cancer detection accuracy increased by 4% compared to [1] and by 7% compared to [2]. This is because a Hamann Indexive Piecewise Linear Regression is applied to a hidden layer of multilayer perceptron learning for analyzing the extracted features with the ground truth features to accurately detect benign and malignant images.

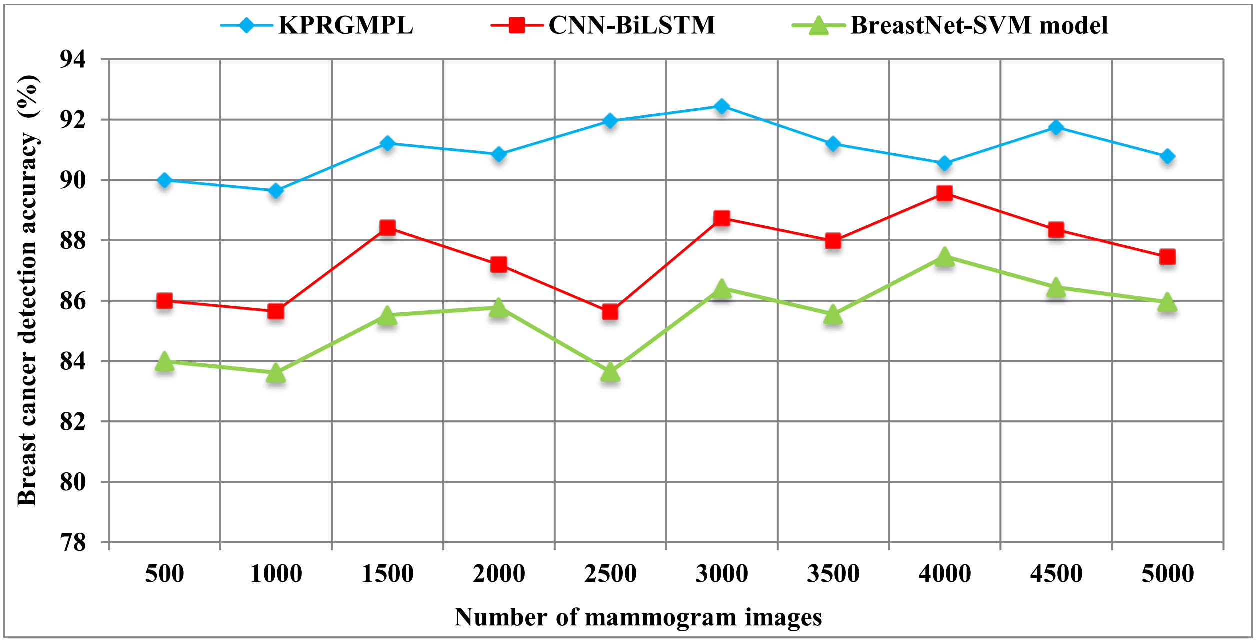

Fig. 5 Graphical illustration of breast cancer detection accuracy versus the number of mammogram images

5.3. Performance Analysis of Precision

It is the measures of true positive detection made by the model. Mathematically, precision is calculated using the following Equation (17),

$$PR = \frac{TRP}{TRP+FLP} \quad (17)$$

Where PR denotes a precision, TRP denotes True Positives, which indicate that the images are correctly detected as normal, benign, or malignant, FLP indicates a false positive, which refers to normal images incorrectly detected as malignant. Table 6 summarizes the comparison of precision with the number of mammogram images. Precision of KPRGMPL is compared with existing CNN-BiLSTM [1] and BreastNet-SVM model [2] in Table 6 and Figure 6 describe a visual comparison of precision versus the number of mammogram images taken in the range from 500 to 5000.

The graph depicts the number of input mammogram images on the 'x' axis and the corresponding precision performance on the 'y axis. The performance of precision was measured using three distinct techniques: KPRGMPL, the existing CNN-BiLSTM [1], and the BreastNet-SVM model [2]. Among these methods, the graph shows that precision performance is increased using the KPRGMPL technique compared to the other two existing methods. This is because the KPRGMPL technique utilizes the Piecewise Linear Regression to estimate the similarity between the extracted features and the ground truth features with the help of the Hamann Indexive function. Based on the similarity value, cancer images and other images are correctly identified. The stochastic gradient function is applied to adjust the weights and minimize the error rate, resulting in improved true positives and minimized false positives in the classification. Comparison of ten averaged results demonstrates that precision performance increased by 5% compared to [1] and by 9% compared to [2], respectively.

Table 6. Comparative evaluation of precision using the proposed KPRGMPL and the existing CNN-BiLSTM [1] and BreastNet-SVM model [2]

Number of mammogram images	Precision		
	KPRGMPL	CNN-BiLSTM	BreastNet-SVM model
500	0.93	0.902	0.886
1000	0.923	0.895	0.875
1500	0.915	0.874	0.856
2000	0.928	0.884	0.866
2500	0.905	0.872	0.857
3000	0.926	0.852	0.839
3500	0.933	0.867	0.822
4000	0.922	0.884	0.847
4500	0.93	0.875	0.834
5000	0.921	0.865	0.825

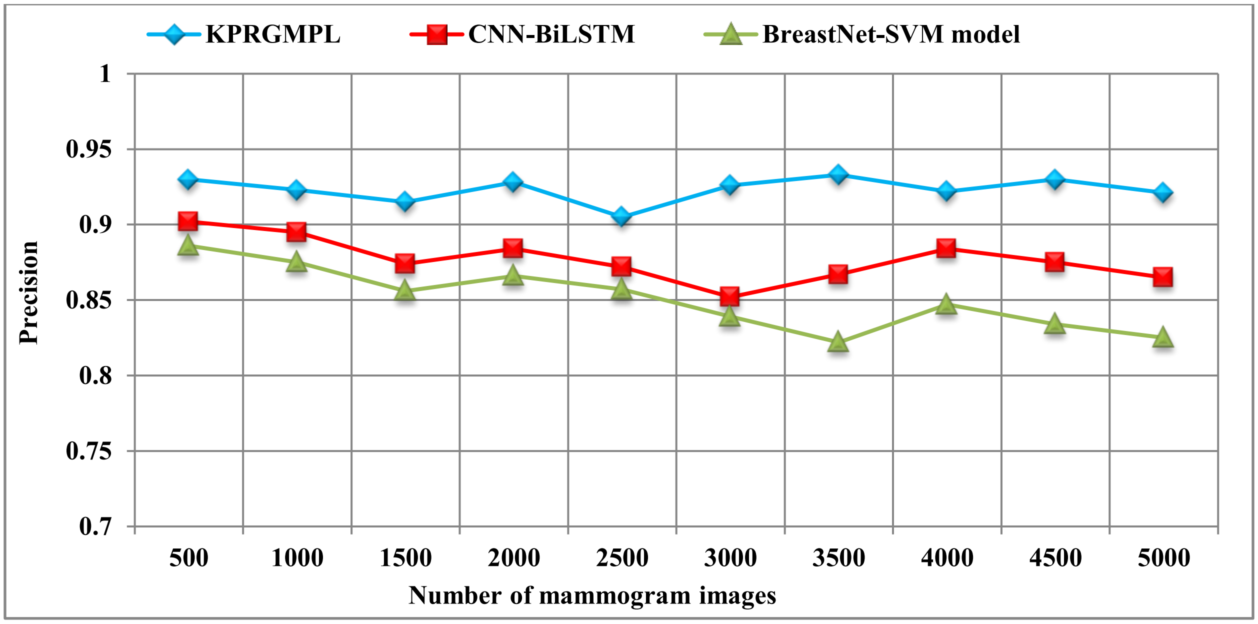

Fig. 6 Graphical illustration of precision versus number of mammogram images

5.4. Performance of Breast Cancer Detection Time

It is measured as the amount of time taken by the algorithm for Breast Cancer Detection from the given input mammogram images. The overall time is formulated in Equation (18),

$$BDT = \sum_{i=1}^{n} MI_i * TM \ [BCD] \quad (18)$$

Where, BDT indicates the breast cancer detection time, TM indicates a time, BCD indicates Breast Cancer Detection of a single Mammogram Image.MI_i'. The overall time of breast cancer detection is measured in Milliseconds (ms). Table 7 summarizes the comparison of breast cancer detection time for 5000 different mammogram images. Breast cancer detection time of KPRGMPL is compared with existing CNN-BiLSTM [1] and BreastNet-SVM model [2] in Table 7. Table 7 and Figure 7 illustrate a graphical analysis of breast cancer detection time with respect to the number of mammogram images ranging from 500 to 5000. The numbers of images collected from the dataset are given in the horizontal direction, while the y-axis represents the breast cancer detection time. The graph illustrates that the breast cancer detection time generally increased for all three methods as the number of images increased. However, the KPRGMPL technique exhibits a minimal breast cancer detection time compared to the existing methods. With the consideration of $'500'$ input breast images for experimentation, the time consumption using the KPRGMPL technique was found to be $'102.5ms'$, while $'111ms$' and $'123.6ms'$ were observed using [1, 2], respectively.

Similarly, different performance results were observed for all three methods. Finally, the performance of the KPRGMPL technique was compared to that of existing methods. The overall comparison results indicate that the time consumption for breast cancer detection was minimized by 9% and 19% using the KPRGMPL technique compared to [1, 2], respectively. This is because of applying radial kernel proximity lambda-connectedness image segmentation in the second hidden layer. This process involves partitioning an entire mammogram image into multiple regions and extracting the Region Of Interest (ROI) to separate specific areas of interest. Subsequently, features such as texture and size, namely area and perimeter, are extracted from the ROI for accurate breast cancer detection with minimal time consumption.

Table 7. Comparative evaluation of breast cancer detection time using proposed KPRGMPL and existing CNN-BiLSTM [1] and BreastNet-SVM model [2]

Number of mammogram images	Breast cancer detection time (ms)		
	KPRGMPL	CNN-BiLSTM	BreastNet-SVM model
500	102.5	111	123.6
1000	115.3	125.6	145.8
1500	121.5	132.8	154.8
2000	130.5	140.2	162.7
2500	142.3	152.3	170.8
3000	153.6	165.8	180.9

3500	163.8	185.7	205.5
4000	178.1	200.4	226.7
4500	189.5	210.7	236.8
5000	201.5	226.9	245.6

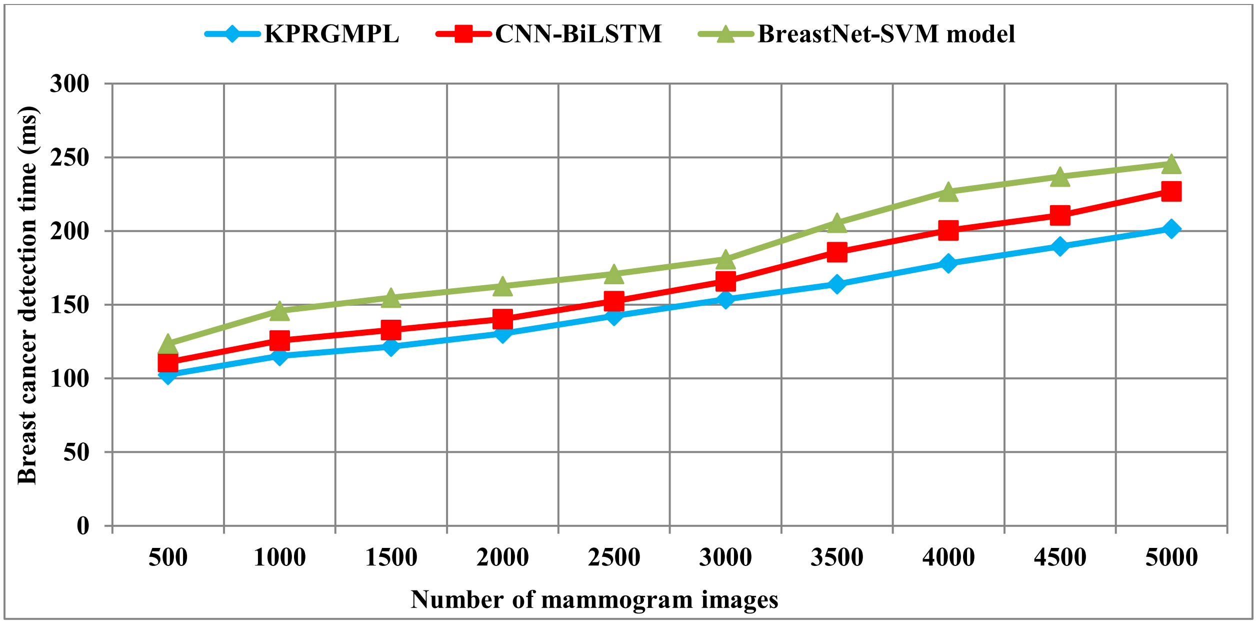

Fig. 7 Graphical illustration of breast cancer detection time versus the number of mammogram images

6. Discussion

This study compares the proposed KPRGMPL method with the existing CNN-BiLSTM [1] and the BreastNet-SVM model [2] using the Breast Cancer Image Dataset based on various parameters, such as PSNR, breast cancer detection accuracy, precision, and breast cancer detection time. In this approach, image preprocessing enhances the image quality by removing noise. Next, the extraction processes are utilized to minimize the time consumption of breast cancer detection. As a result, it achieves better accuracy in detecting and classifying cancer with fewer errors. The outcomes confirm that the KPRGMPL method improves the breast cancer detection accuracy by 5%, 9% of PSNR, and 7% of precision, with 14% of minimum breast cancer detection time when compared to different existing methods.

7. Conclusion

Breast cancer is increasing rapidly owing to the irregular growth of cells. Manual cancer diagnosis from mammogram images is also complex for radiologists and medical professionals. This paper proposes a novel KPRGMPL technique for accurate Breast cancer detection from mammogram images with minimal time consumption. The KPRGMPL technique first performs image preprocessing to enhance image quality by removing noise, resulting in an increased peak signal-to-noise ratio. Following this, the segmentation, ROI identification, and feature extraction processes are carried out using the KPRGMPL technique to minimize the time consumption of breast cancer detection. Finally, the KPRGMPL technique achieves higher accuracy in detecting and classifying cancer with minimal error. A comprehensive simulation was conducted using the CBIS-DDSM: Breast Cancer Image Dataset, and various performance metrics such as peak signal-to-noise ratio, breast cancer detection accuracy, precision, and breast cancer detection time were measured. The comparative analysis shows that the KPRGMPL technique outperforms existing methods in achieving higher accuracy, peak signal-to-noise ratio, and precision, as well as reducing breast cancer detection time.

The limitation of breast cancer detection employed to enhance the accuracy with mammograms, the main screening tool, is that it misses some cancers and infrequently produces false positives. The different factors are dense breast tissue, the size and location of a cancer, and variations in skill between examiners, which also impact detection. In addition, screening failed to avoid cancer growth or ensure survival, and interval cancers (those developing between screenings) can occur. In the future, the leading rate will be more precise, modified, and efficient recognition and diagnosis. It potentially improves the detection accuracy with minimum false positives. Emerging imaging technologies like MRI and ultrasound will also play a significant role in complementing conventional Mammography, particularly for women with dense breast tissue.

Declarations

Data Availability Statement

CBIS-DDSM: Breast Cancer Image Dataset is available within the article.

The dataset was gathered from https://www.kaggle.com/datasets/awsaf49/cbis-ddsm-breast-cancer-image-dataset.

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