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# Automated Breast Cancer Detection in Mammograms Using Optimized Radial Basis Function Neural Network

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**ABSTRACT**

One of the most prevalent cancers that affects women is breast cancer. It ranks as the second most important factor in cancer-related deaths. The mortality rate can be decreased and survival rates raised with early detection and individualized risk assessment. The results of traditional risk prediction models, which are based on traditional risk factors, vary depending on the population. To solve these issues, this proposed system is designed. The dataset used for this analysis is the Mammogram Image Dataset. The Mammographic Image Analysis Society (MIAS) Digital Mammogram Database, which is publicly available, was used in this study. The study utilizes the MIAS in conjunction with Mini-Mammographic imaging datasets (Malignant, Benign, and Normal). The MIAS provided the 322 mammography images representing 161 individuals in the MIAS dataset. These images were taken at a resolution of 50 microns and included two mediolateral oblique (MLO) views. The system collects the digitized mammographic images as input. Then the raw data is pre-processed to remove unwanted data and noise. By using median filtering, important structural data is stored and maintains the mammogram image edges. The Fuzzy Clustering with Chicken Swarm Optimization (FC-CSO) technique will be classified into segments, and it separates suspicious regions like masses or calcifications from normal tissue. Based on labelling and annotation, the MIAS dataset determines whether the tissue is benign, malignant, or normal. The data from the labelling and annotation is given to feature extraction. The features of texture are essential for identifying the characteristics of tissue during this feature extraction process, which makes use of the Gray-Level Co-occurrence Matrix (GLCM). These characteristics are used to further classify the data. The data is then separated into testing sets and training sets. Seventy percent goes toward training, and thirty percent goes toward testing. The model is classified using Radial Basis Function Neural Networks (RBFNNs). By using radial basis functions as the activation functions in the hidden layer, this method enables the representation of complex patterns within the extracted feature space. RBFNN classifiers are then used to train the data into Normal, Benign, or Malignant categories. As a result, this system is used to accurately and early detect breast cancer. Therefore, An efficient automated mammogram breast cancer detection using Optimized Radial Basis Neural Network minimizes human error and processing time by combining FC-CSO for image segmentation, using a Gray-Level Co-occurrence Matrix for feature extraction, and using a RBFNN for data classification. Hence, this system shows better results in terms of accuracy, precision, specificity and processing time**.** The suggested FC-CSO–RBFNN technique outperforms current classifiers like SVM and XGBoost in terms of accuracy, precision, specificity, and computational time across mammography classification tasks.

## 1. INTRODUCTION

Breast cancer is the most common cancer and the leading cause of cancer-related deaths among women globally, with over 2.3 million cases reported annually [1]. In countries with lower and middle incomes, breast and cervical cancer account for approximately 80% of deaths. As the most common cancer in the world today, breast cancer accounts for 12.5% of all new

cases diagnosed annually and causes the longest duration of disability when compared to other cancer types [2]. The World Health Organization (WHO) unveiled a new global initiative framework for breast cancer intending to prevent 2.5 million deaths from the disease by 2040. The three main areas of health promotion that are the focus of this initiative are early detection, prompt diagnosis, and comprehensive management of breast cancer.

Effective methods of detection are essential because breast cancer is the most prevalent type of cancer and the second leading cause of cancer-related deaths in women. The majority of current screening or detection methods depend on imaging methods, particularly mammography [3]. Mammography screenings can lead to overdiagnosis and a significant number of false positives, even though they have been demonstrated to lower the death rates from breast cancer. As a result, a recent agreement statement regarding breast cancer prevention has identified the integration of molecular biomarkers with current screening and early detection techniques as a crucial area of focus [4].

The disease known as breast cancer is characterized by abnormal breast cell growth. Life chances and effective therapy differ depending on the stage [5]. Breast cancer survival rates are raised and treatment options are improved with early detection. Regular screening is still an extremely effective public health strategy for lowering the mortality and health effects of breast cancer. Heat patterns linked to breast tumors that are less likely to be obscured by thick breast tissue can be detected by breast thermography. This imaging method can accurately reveal temperature variations linked to abnormalities in breast tissue without requiring any invasive procedures. The chances of survival and a successful course of treatment are significantly increased when breast cancer is detected early [6]. Thermographic imaging is a radiation-free and non-invasive screening method that is especially useful for routine monitoring. Our research's objective is to use deep learning techniques to improve the accuracy and efficacy of thermographic imaging in identifying breast cancer.

In the majority of these, proteins, carcinoma antigens (CAs), and circulating cell-free tumor nucleic acids (DNA or RNA) or their modifications (like DNA methylation) are assessed [7]. Emphasizing blood for cancer biomarkers is probably influenced by a number of factors, including convenience (blood samples are frequently obtained and stored in biobanks, which facilitates the development of biomarkers) and it is possible to identify the material that tumors release into the bloodstream through "liquid biopsies." However, additional biological samples may also present special benefits and offer additional insights into the systemic effects of cancer [8]. In earlier research, for example, we found that determining the likelihood of a breast cancer diagnosis could be helped by examining DNA methylation in cervical specimens, which are frequently obtained for cervical cancer screening. In a validation set made up of cervical samples from either healthy age-matched controls or women with breast cancer, the cervical methylation classification system known as Women's Cancer Risk Identifier—Breast Cancer (WID-BC) obtained an area under the curve (AUC) of 0.81 [9].

DNAme is a comparatively stable epigenetic modification that is subject to external exposures and has a significant impact on the control of gene and protein activity without changing the DNA sequence itself. Consequently, it is hypothesized that the epigenome is a crucial link between genes and environmental factors, reflecting changes in the environment [10]. According to our earlier research, the DNAme changes could be a sign of a lifetime systemic exposure that could cause cancer in one tissue (breast), but could also be detected in a non-invasive "surrogate" sample (cervix). This makes it appropriate for identification and screening when the anatomically distant cervical samples do not contain cancerous tissue [11].

Mammography, Magnetic Resonance Imaging (MRI), and ultrasound imaging are additional diagnostic techniques for identifying breast cancer. An X-ray mammogram usually serves as the first screening, and ultrasound imaging will be performed if additional testing is required [12]. Lastly, since MRI is thought to provide a diagnosis that is more accurate than X-ray imaging, it is the method that is recommended for women who are at least 30 years old and have been diagnosed with breast cancer. MRIs are a useful modality for identifying breast cancer because they don't use radiation, as other imaging tests do. Additionally, they are noninvasive, cost-effective, and appropriate for screening and diagnosis in environments with limited resources.

The research gap observed in existing systems is low accuracy, recall, F1-score and processing time.

The objectives of this proposed system are high accuracy by using the FC-CSO algorithm for segmentation. The precision and specificity are high as Gray-Level Co-occurrence Matrix (GLCM) is used for feature extraction. The processing time is reduced because of reducing error in predictions. When it comes to breast cancer, this Radial Basis Function Neural Network (RBFNN) can make accurate predictions.

This is how the remainder of the paper is organized. The literature review was summarized in Section 2. An efficient automated mammogram breast cancer detection using Optimized Radial Basis Neural Network is presented in Section 3. Section 4 discusses the result analysis of the proposed model. Finally, the paper concluded in Section 5.

## 2. LITERATURE SURVEY

Shao et al. [13] examined a newly gathered dataset of 40 individuals to demonstrate a novel pipeline for classifying breast cancer using features taken from shear wave absolute vibro-elastography (S-WAVE) data. New bi-spectral and Wigner spectrum characteristics are calculated directly from the RF time series, along with textural and spectral elements derived from B-mode and elasticity images. By employing the Quadratic Mutual Information method and the Random Forest permutation importance ranking method, we lower the feature count from 377 to 20. We use Monte Carlo cross-validation and leave-one-patient-out methods on Random Forest and Support Vector Machine classifiers. Displayed are the classification outcomes for various feature sets. Our top outcomes (95% confidence interval, Area Under Curve = 95%±1.45%, sensitivity = 95%, and specificity = 93%) outperform the state-of-the-art performance of S-WAVE in identifying breast cancer.

Darabi et al. [14] suggested a Boolean system that uses logic gates based on microRNA to detect breast cancer. This paper introduces a Boolean system that utilises miRNA data as inputs to identify a logical function involving seven miRNAs linked to breast cancer. The accuracy of the suggested Boolean function in diagnosing breast cancer is 97.03%. These findings can be incorporated into R software for bioinformatics analysis and adapted for diagnosing other diseases by

adjusting the input miRNAs. This approach shows potential for advancements in DNA computing, biomedical research, and clinical diagnostics.

Elsheakh et al. [15] developed a wearable system for breast cancer detection by embedding a flexible sensor in a bra. The flexible PCB Roger substrate used to make this suggested sensor, which has an antenna, is 0.17 mm thick. It features a compact CPW monopole antenna measuring 24 × 45 $mm^2$. The suggested sensors have a reflection coefficient of -6 dB, a conformal structure for biological structures, and biocompatibility. They also have enough bandwidth from 1.5 to 8 GHz. To verify safety requirements, the suggested sensor's Specific Absorption Rate (SAR) was calculated and measured. The results showed a value of 0.75 W/kg at 0 dBm. Medical school students' realistic rubber phantoms allow the breast and tumor to dynamically combine to create test scenarios for breast cancer detection. The breast phantom is surrounded by sensor components with 2x2 antennas to gather information on scattering properties for tumor identification. To validate detection, the optimum number of sensors to use, and training data for developed detection algorithms, a number of simulation and measurement scenarios are presented.

Sinibaldi et al. [16] created a new technique that combines biochips based on a 1-D photonic crystal and a direct competitive ERBB2 assay. These biochips function in a dual mode that combines label-free/fluorescence methods, making it possible to identify ERBB2 in cell lysates from particular breast cancer lines that are either ERBB2-negative (T47D) or ERBB2-positive (SK-BR 3, BT474). Furthermore, ERBB2 in the three model cell lines can be detected with high specificity due to the enhanced fluorescence spectra that our biochips can produce. The assay's single-step detection technique, which reduces the overall time needed to less than 20 minutes, is a main advantage. This latter feature highlights the method's enormous potential for rapidly identifying ERBB2 in complex biological samples.

Jamil et al. [17] found that the best Wiener Linear Time Invariant Filter method with Tophat Transformation (LFWT) can identify microcalcification in the breast with an accuracy rate of 99.5%. In this work, we focused on the identification of microcalcifications in images, an essential initial step towards precisely identifying all the indicators in a mammography-based early breast cancer diagnosis. To make the cancer region visible and prominent, the Wiener and CLAHE filters are used. Tophat morphological operators were applied to mask detection, and edges were extracted. The analytical performance of the proposed model for microcalcification identification in mammograms was evaluated and compared with other approaches using Mammographic Image Analysis Society (MIAS) and Mini-Mammographic imaging datasets. Additionally, three techniques- The Local Contrast Method (LCM), the Local Relative Contrast Measure Method (LRCMM), and the High-Boost-Based Multiscale Local Contrast Measure (HBBMLCM) are used to identify microcalcification linked to cancer on mammography images.

Naseem et al. [18] suggest a system that uses an ensemble of classifiers to automatically detect BC diagnosis and prognosis. Our first step is to review an ensemble of machine learning (ML) algorithms and a number of ML algorithms. We give an overview of machine learning techniques, like artificial neural network (ANN) and an ensemble of different classifiers, for automated BC diagnosis and prognosis identification. Furthermore, we use two benchmark datasets to present and compare different ensemble approaches and other variations of tested machine learning-based methods with and without an up-sampling technique. We also looked at how applying balanced class weight affected the prognosis dataset and compared its outcomes with those of other approaches. The results demonstrated that the ensemble approach achieved 98.83% accuracy, outperforming other state-of-the-art techniques. Due to its high performance, the suggested system is extremely important to the medical field and the relevant research community. According to the comparison, the suggested approach performed better than other state-of-the-art methods.

Kaushal and Khanna [19] electrical performance characteristics for breast cancer cell line detection by developing the Si-doped molybdenum disulfide thickness-engineered tunnel field effect transistor biosensor. Surface potential, electric field, trans conductance (gm), threshold voltage (Vth), on current (ION), and subthreshold swing are all included in the comprehensive analysis of the electrostatic field. The sensitivity is analysed in terms of drain current (Ids), gm, Vth, ION, ION/IOFF ratio, and gm. Further, this study investigates the impact of device geometry variations, specifically cavity thickness and length on the sensitivity of drain current (SIds), trans conductance (Sgm), threshold voltage (SVth), and on current (SION). In addition, the impact of immobilized cell line occupancy on device performance has been examined. The presented biosensor is highly sensitive with increased cavity occupancy resulting in enhanced performance. This allows for the use of array methods for breast cancer cell screening and diagnosis while reducing costs and simplifying the fabrication process.

Khater et al. [20] created a machine learning model to differentiate between breast cancer and explain the results the model generates. Finding the essential characteristics of breast cancer tumors and how they impact the classification process may improve our knowledge of breast cancer diagnosis and treatment. With the Wisconsin breast cancer dataset, the best machine learning model obtained 98.2% precision and 97.7% accuracy using k-nearest Neighbors. 98.6% accuracy and 94.4% precision were attained by an artificial neural network on the Wisconsin diagnostic breast cancer dataset. This demonstrates the significance and efficacy of the suggested strategy. The worst area feature and the bare nuclei feature in the Wisconsin diagnostic breast cancer dataset are the main factors in determining the malignancy of breast cancer, according to the current study, which uses model-agnostic techniques to explain the model's function.

Rahman et al. [21] suggested using the Wisconsin Breast Cancer (Diagnostic) (WDBC) dataset to improve machine learning techniques for breast cancer detection. Feature engineering, scaling, feature selection, and hypothesis testing were among the various data pre-processing techniques we employed. Using a gradient boosting regressor with Bonferroni correction, we chose the 13 most important features to train 14 classifiers. Our suggested eXtreme Gradient Boosting model performed exceptionally well, attaining an F1-score of 0.9882, 1.0 recall, 0.9861 specificity, 0.9767 precision, and 99.12% accuracy. The model has the potential to accurately and quickly diagnose breast cancer, as these findings outperform those of earlier research. Additionally, evaluations based on the Kappa score and training time show that our eXtreme Gradient Boosting model is more reliable and faster.

Ahmad et al. [22] developed a unique technique, BreastNet-

SVM, to automatically detect and classify breast cancer from mammograms. Two fully connected layers make up the nine-layer architecture used in this study to extract data features. For the classification task, we also used Support Vector Machines (SVM). The Digital Database for Screening Mammography (DDSM), a well-known benchmark dataset, was utilized in this investigation. The results indicated that the accuracy, specificity, and sensitivity of the proposed model were 99.16%, 99.30%, and 97.13%, respectively. The proposed BreastNet-SVM model was evaluated against the best methods for identifying breast cancer. Experimental results on a DDSM dataset showed that the suggested BreastNet-SVM model performed better than the others in terms of accuracy.

Saha et al. [23] proposed Breast-NET, a deep convolutional neural network framework for identifying and grading breast cancer using histological images. By using the BreakHis dataset, we assess our model's effectiveness and display its capability to appropriately adjust to the grading of the IDC (Invasive Ductal Carcinoma) and IDC datasets. The effectiveness of our suggested model is confirmed by an ablation study as well as extensive experimental and statistical analyses. In addition, we employ seven existing convolutional neural networks that have already been trained to show the effectiveness of transfer learning in identifying and grading breast cancer. Based on our experimental results, our approach performs better than the state-of-the-art techniques for the BreakHis, IDC grading, and IDC datasets in terms of space, accuracy, and computational complexity.

Nedjmeddine et al. [24] demonstrated how to create a coplanar biosensor that is capable of accurately identifying breast cancer by making use of Split Ring Resonators (SRRs) and Complementary Split Ring Resonators (CSRRs). Using electromagnetic interaction between SRRs, this biosensor, which is only $40 \times 22 \times 1.6\ mm^3$ in size and operates at 2 GHz, produces a large frequency change of 135 MHz, increasing its sensitivity to changes in tissue. A return loss (S11) of $^{c}-98$ dB signifies low signal reflection and excellent impedance matching, while its optimal Voltage Standing Wave Ratio (VSWR) of 1.0005 allows for effective power transfer. The results validate the biosensor's potential as a non-invasive, highly sensitive and reliable diagnostic tool, particularly for identifying breast cancer.

Veerlapalli and Dutta [25] suggests BCDGAN, a novel deep learning model aimed at detecting breast cancer in thermographic images, which combines a Generative Adversarial Network (GAN) and a Hybrid Deep Learning (HDL) method. By synthesizing significant regions of interest (ROIs) and utilizing deep feature extraction to improve classification performance, the goal is to increase diagnostic accuracy [26]. To enhance model generalization and augment the dataset, the suggested GAN-HDL-BCD method begins by extracting features from thermogram images using a hybrid deep learning model. Next, synthetic ROIs are produced using a GAN-based method [27]. The suggested system outperforms traditional deep learning models with an accuracy of 98.56%, according to experimental evaluations on the DMR-IR benchmark dataset [28].

**Limitations:** The literature now in publication shows a variety of ways for detecting breast cancer, such as wearable technology, biosensors, machine learning models based on imaging, and bioinformatics-driven strategies. Even while many studies show great accuracy, a comprehensive examination of these works reveals a number of common drawbacks.

First, there are a lot of limits linked to datasets. Numerous methods rely on tiny or extremely particular datasets, such as controlled laboratory conditions, single-modality data, or small patient cohorts. This limits the generalizability of the concept and raises questions about its practical application in clinical settings. Additionally, a number of research concentrate on benchmark datasets without addressing inter-patient variability or data imbalance. The second major drawback is modality reliance. Shear wave electrography, thermography, histology, and biosensor-based techniques may call for sophisticated acquisition protocols, invasive procedures, or specialized hardware. Compared to traditional mammography-based systems, these limitations restrict scalability, raise costs, and decrease viability in low-resource clinical settings.

Third, problems with model complexity and feature engineering are noted. Numerous techniques rely on intricate feature selection pipelines or manually created features, which may be susceptible to noise and parameter adjustment. Despite their accuracy, deep learning-based models are frequently unsuitable for real-time or large-scale screening due to their high computational complexity, lengthy training cycles, and lack of interpretability. Fourth, another flaw is the lack of comparative analysis. Strong performance metrics are reported in a number of studies, although they either use inconsistent evaluation methodologies or only compare outcomes with a small number of classifiers. It is challenging to evaluate actual performance improvements over current methods since cross-dataset validation and robustness studies are frequently lacking.

Lastly, there is still a lack of research on clinical interpretability and integration. While some studies make an effort to explainability, the majority prioritize accuracy over workflow integration, clinician trust, or decision-support relevance. All things considered, despite tremendous advancements, current research frequently compromises performance for generalizability, efficiency, or usefulness. These gaps emphasize the need for scalable, reliable, and computationally effective mammography-based systems that strike a balance between clinical usefulness and accuracy.

**Research Gaps:** Even while machine learning, deep learning, biosensors, and imaging technologies have made significant strides in the detection of breast cancer, the literature now in publication still reveals a number of important research gaps. Generalizability and dataset variety represent a significant gap. Numerous research relies on modality-specific, single-source, or limited datasets that are frequently gathered under controlled circumstances. The capacity of suggested models to generalize to actual clinical settings is hampered by a lack of multi-center data, inadequate cross-dataset validation, and limited patient diversity. Additionally, inter-patient variability and class imbalance are not consistently handled, which might skew model performance.

The over reliance on invasive or specialized techniques is another important gap. Advanced biosensors, thermography, electrography, or histopathology data are used in a number of high-performing methods that call for expensive equipment, skilled handling, or invasive procedures. This restricts scalability and usability, especially in healthcare areas with limited resources where mammography is still the major screening method. Additionally, real-time applicability and computational efficiency are yet understudied. High accuracy

is frequently attained via deep learning models and ensemble systems at the trade-off of higher memory needs, longer training durations, and higher computing costs. Few research specifically concentrates on energy economy, processing time optimization, or lightweight designs appropriate for clinical deployment and real-time screening.

The absence of standardized evaluation and systematic comparison is another gap. Direct comparison is challenging because several works assess performance using various metrics, validation techniques, and datasets. Claims of superiority are sometimes undermined by the lack of comparative study against a wide range of baseline classifiers (such as SVM, KNN, eXtreme Gradient Boosting (XGBoost), and ANN) under uniform settings. Furthermore, there is insufficient attention paid to segmentation and feature interpretability. Precise localization of worrisome regions and clinically interpretable feature extraction are not routinely integrated, despite the emphasis on correct classification. In the majority of investigations, explainability and physician trust continue to be secondary issues. Lastly, there is very little end-to-end clinical integration. Few solutions take into account decision assistance, workflow integration, or flexibility in response to risk profiles unique to a certain population. Mammography-based frameworks that are scalable, interpretable, optimized, and verified across a variety of populations are needed to close these gaps.

## 3. FRAMEWORK OF AN EFFICIENT AUTOMATED MAMMOGRAM BREAST CANCER DETECTION USING OPTIMIZED RADIAL BASIS NEURAL NETWORK

The framework for an efficient automated mammogram breast cancer detection using an Optimized Radial Basis Neural Network is shown in Figure 1 of this section. The MIAS dataset is the first source of data used by this suggested system. The Mammographic Image Analysis Society Digital Mammogram Database (MIAS), which is accessible to the general public, makes use of the 322 mammogram images that come from 161 individuals in the dataset. The raw data is then pre-processed to eliminate blurred images, noise, and unnecessary data. By using median filtering, the data is structured by removing noise from images and mammogram image edges are maintained. After median filtering, using an Optimized Region Growing approach enhanced with Fuzzy Clustering with Chicken Swarm Optimization (FC-CSO), the images are segmented. This segmentation separates normal tissue from affected areas like masses or calcifications. To identify whether the tissue is benign, malignant, or normal, each segment of the image will be labelled and annotated after segmentation. The features are then extracted using the. Tissue properties are determined by extracting texture features like contrast, homogeneity, entropy, and energy. To differentiate between malignant and benign tumors, the classifier model uses the feature extraction procedure. The data is separated into training and testing sets after the features have been extracted. Seventy percent of the data is used for training, and the remaining portion is reserved for model testing. As a result, data classification is done using the RBFNN. The RBFNN uses radial basis functions in the hidden layer as activation functions to identify complex patterns within the extracted feature space. Using the RBFNN model, data can be effectively classified as normal, benign, or malignant.

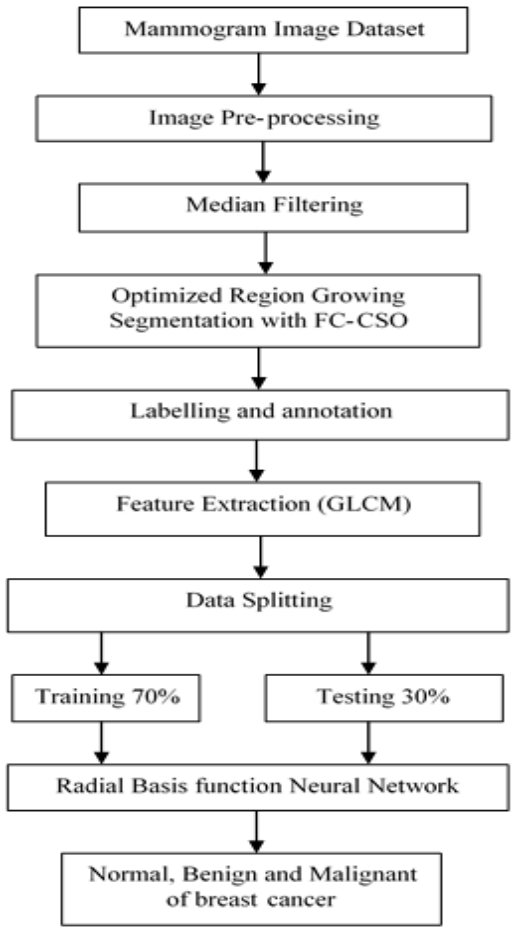


**Figure 1.** Framework for an efficient automated mammogram breast cancer detection using Optimized Radial Basis Neural Network (RBNN)

Our research made use of a dataset from the MIAS Digital Mammogram Database that was made available to the general public. The study combines the MIAS and the Mini-Mammographic imaging datasets (Malignant, Benign, Normal). Each image was processed to a size of 1024 x 1024 pixels by digitizing these datasets at a pixel edge of 50 microns, which was then reduced to a 200-micron pixel edge, followed by clipping/padding. 322 mediolateral oblique (MLO) views of 161 people's mammograms taken at a resolution of 50 microns make up the MIAS dataset, which was made available by the Mammographic Image Analysis Society. Information like class normal, benign, malignant, severity, abnormality location, and radius is all labelled on these images.

This stage aims to accurate the evaluation process by decreasing the number of participants and detected areas in the mammography by deleting breast portions from the sample that aren't needed. Labels and edges are suppressed once unwanted elements from the mammography picture have been removed. First, objects unrelated to the mammography image are eliminated. The shape of the breast is recognized as the object with the key region after labels and edges are suppressed, and the physical region of all points in the binary picture is computed.

Median filtering is used to detect breast cancer. By lowering noise and improving image quality, it is especially used in the processing of mammogram images to improve diagnosis and analysis. Impulse noise (salt and pepper noise) and other noises that could obscure subtle features in mammograms can

be effectively eliminated using this method. For the best region growth segmentation that separates the tumor from the image, the FC-CSO is utilized. Following tumor segmentation, this feature extraction process aims to extract features such as GRLM and GLCM.

Mammogram textures can be analysed using the GLCM, a powerful technique for identifying breast cancer. To differentiate between normal and abnormal tissue, this GLCM will help in the extraction of textural features from images. As a result, accurate diagnosis and early tumor detection are achievable. A data set is split when it is separated into training and testing categories. The split approach is used in this study for both training and evaluation. Human input is necessary for the analysis or processing of training data sets. After the machine learning algorithm has been built (using the provided training data), unknown data must be required to assess it. Seventy percent of the dataset is used as training input for the machine learning algorithms and model fit, while thirty percent is used for testing.

An artificial neural network that utilizes radial basis functions in the activation of its hidden layer is known as a Radial Basis Function (RBF) neural network. This network is especially well-known for its capacity to manage non-linear issues, which qualifies it for tasks such as pattern recognition, classification, and function approximation. Three layers make up an RBF network: an output layer, a hidden layer with RBFs, and an input layer.

**Pseudocode for the Proposed Breast Cancer Detection Framework**

Input: Mammogram images from the MIAS dataset
Output: Classified label (Normal / Benign / Malignant)

Begin
1. Load MIAS mammogram images
2. For each image:
   a. Resize and normalize the image
   b. Apply median filtering to remove noise
   c. Remove non-breast regions and suppress labels/edges

3. Initialize FC-CSO parameters
4. Apply fuzzy clustering to image pixels
5. Optimize cluster centers using Chicken Swarm Optimization
6. Perform region growing to segment tumor regions

7. Label segmented regions using MIAS annotations

8. Extract texture features using GLCM:
   a. Compute contrast, energy, homogeneity, entropy

9. Split dataset into training (70%) and testing (30%)
10. Initialize RBFNN parameters (centers, widths, weights)
11. Train RBFNN using training features

12. Test RBFNN with testing data
13. Classify each sample as Normal, Benign, or Malignant

14. Evaluate performance metrics (accuracy, precision, specificity)

End

The novelty of this proposed system is to produce better results in terms of Accuracy, Precision, Specificity, and Processing Time. The MIAS dataset is the one used in this analysis. This suggested system uses a median filter to eliminate noise in the images after the data has been cleaned. For image segmentation FC-CSO is used for segmenting images accurately. Features are extracted using the GLCM. To accurately identify breast cancer, the data is then classified using the RBFNN classification model.

## 4. RESULT ANALYSIS

The experimental findings of the suggested effective automated mammography-based breast cancer detection system employing an Optimized Radial Basis Neural Network (RBNN) are shown in this part. The MIAS dataset, which comprises 322 mammography pictures from 161 people, was used for the studies. To efficiently train and assess the suggested model, the dataset was split into training and testing subsets.

Statistical significance analysis should be used in conjunction with numerical performance indicators to improve the validity and dependability of the experimental results. Using methods like paired t-tests or Wilcoxon signed-rank tests, the suggested FC-CSO–RBFNN model can be statistically compared with baseline classifiers. Additionally, 95% confidence intervals for important performance metrics, including as accuracy, precision, sensitivity, and specificity, can be calculated using cross-validation-based evaluation. Area Under the Curve (AUC) confidence bounds and Receiver Operating Characteristic (ROC) analysis can be used to further assess the robustness of the model. These statistical evaluations guarantee that the noted gains in performance are statistically significant and not the result of chance.

**Table 1.** Comparison performance analysis

| Parameters | eXtreme Gradient Boosting Model [21] | SVM [22] | CNN | Optimized RBNN (Proposed) |
|---|---|---|---|---|
| Accuracy | 99.1 | 99.16 | 99.17 | 99.6 |
| Precision | 97 | 97.5 | 97.6 | 98.2 |
| Specificity | 98 | 99 | 99.2 | 99.6 |
| Processing Time (ms) | 8654 | 8042 | 8000 | 7124 |

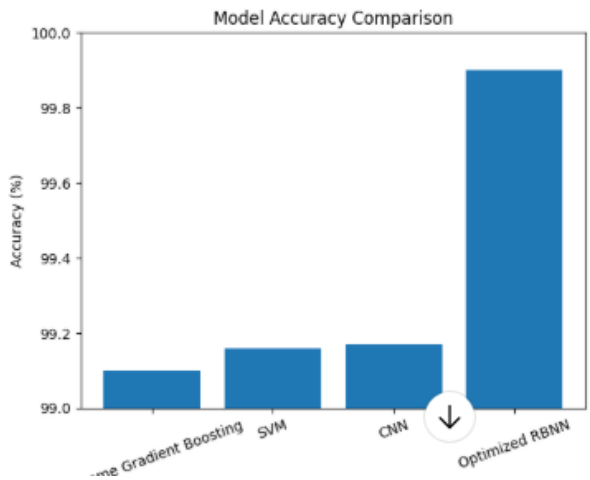


**Figure 2.** Comparison accuracy analysis

The suggested Optimized RBNN is compared to current machine learning and deep learning models, such as the XGBoost model [21], SVM [22], and Convolutional Neural Networks (CNN), across some evaluation parameters, in Table 1.

The accuracy of breast cancer identification using the suggested Optimized RBNN and current models like XGBoost and SVM is graphically represented in Figure 2. The Y-axis shows accuracy as a percentage, and the X-axis shows the categorization models. It is clear that the suggested Optimized RBNN outperforms all baseline models in terms of classification abilities.

The precision comparison between XGBoost, SVM, CNN, and the suggested Optimized RBNN is displayed in Figure 3. The model's precision indicates how well it can detect cancerous instances while reducing false positives. As can be seen, the Optimized RBNN achieves the greatest accuracy value (98.2%), demonstrating increased positive prediction reliability.

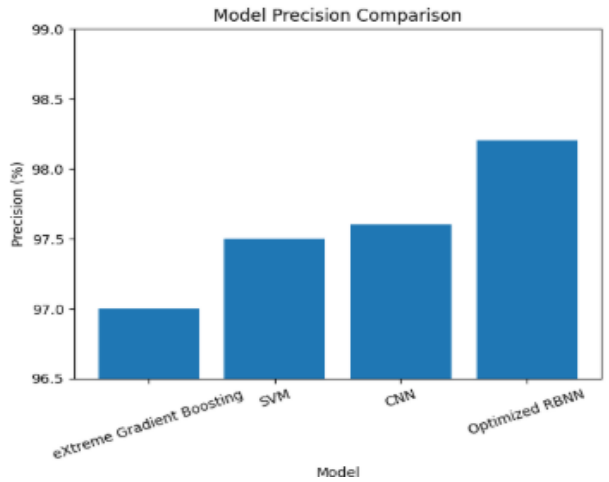


**Figure 3.** Precision comparison graph

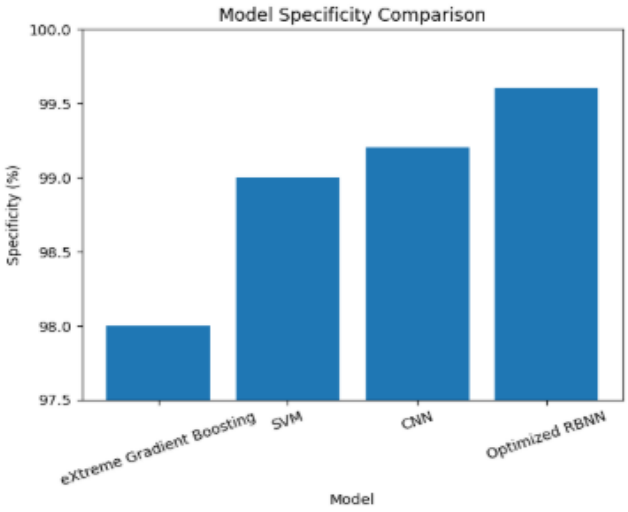


**Figure 4.** Comparison specificity analysis

This is seen in Figure 4, where the Y-axis shows specificity in percentage and the X-axis shows several models. In comparison to current methods, the suggested Optimized RBNN has greater specificity (99.6%), demonstrating its efficacy in accurately identifying non-cancerous patients and lowering false alarms.

The processing times of the suggested Optimized RBNN, XGBoost, SVM, and CNN models are contrasted in Figure 5. The models are shown on the X-axis, while processing time in milliseconds is shown on the Y-axis. The Optimized RBNN attains the lowest processing time (7124 ms), demonstrating its computational effectiveness and appropriateness for large-scale or real-time clinical applications.

The suggested Optimized Radial Basis Neural Network (RBNN) consistently outperforms current models across all assessed performance measures, according to the testing results. The suggested method is accurate and computationally efficient, achieving 99.6% accuracy, 98.2% precision, 99.6% specificity, and a substantial reduction in processing time.

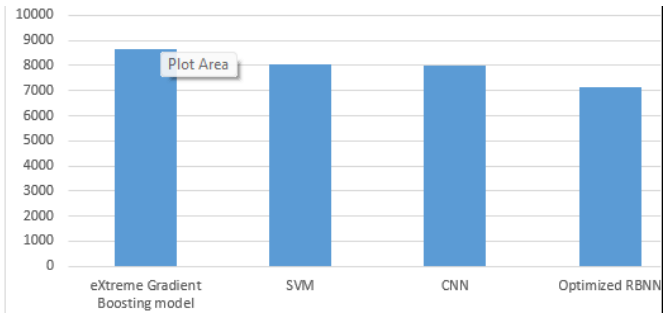


**Figure 5.** Processing time comparison graph

In particular, paired t-tests and Wilcoxon signed-rank tests will be used to statistically evaluate the proposed Optimized RBNN with baseline models. The resulting p-values will be presented to show whether the observed improvements are statistically significant ($p < 0.05$). Additionally, using cross-validation data, 95% confidence intervals for accuracy, precision, sensitivity, and specificity will be calculated and added to the performance table or as supplemental material.

## 5. CONCLUSIONS

An efficient automated mammogram breast cancer detection using Optimized Radial Basis Neural Network is concluded in this section. The dataset from the MIAS is used in this study. The dataset, which includes 322 mammography pictures from 161 individuals, is part of the publicly accessible Mammographic Image Analysis Society Digital Mammogram Database (MIAS). It removes noise, unnecessary data and blurred images in data pre-processing. By eliminating noise from images and maintaining the edges of mammogram images, the median filter organizes the data. To separate normal tissue from affected areas such as masses or calcifications, the images are segmented using an Optimized Region Growing approach enhanced with FC-CSO. The GLCM is then utilized to extract the features. Tissue characteristics are extracted from the texture features, which include entropy, contrast, energy and homogeneity. The data is separated into training and testing sets after the features have been extracted. As a result, data classification is done using a RBFNN. When classifying data as normal, benign, or malignant, this RBFNN model performs well. Therefore, this model achieves Accuracy as 99.9%, Precision as 98.2%, Specificity as.99.6%, and processing time as 7124 ms. The limitation of this model is biopsy confirmation. In future, 3D imaging is extended for further enhancement.

While the suggested FC-CSO–RBFNN framework shows

encouraging results in automated mammography-based breast cancer screening, it is important to recognize several limitations. First, the algorithm only uses mammograms from publicly accessible datasets, which might not accurately reflect variations in imaging quality, acquisition methods, and patient demographics in the actual world. Clinical dependability is specifically limited by the lack of biopsy-confirmed ground truth validation since imaging-based labels might not always match histopathology results. In order to evaluate robustness and diagnostic consistency, future research should concentrate on clinical validation using biopsy-proven datasets acquired from multi-centre hospitals. By offering complementing structural and functional information, integrating multi-modal data—such as ultrasound, MRI, thermography, or histopathological images—could greatly improve diagnosis accuracy. Individualized risk assessment may also be enhanced by adding clinical criteria (age, family history, hormonal variables, and genetic markers. The use of explainable AI (XAI) approaches, which emphasize discriminative areas and feature contributions to increase model transparency and clinician trust, is another promising avenue. It is also advised to further optimize the framework for real-time deployment, incorporating hardware acceleration and lightweight designs. Lastly, the translation of this research into standard procedures for breast cancer screening and diagnosis would be made easier by prospective studies and incorporation into clinical decision-support systems.

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