African Journal of Applied Research
Vol. 12, No. 4 (2026), pp.413-437
http://www.ajaronline.com
https://doi.org/10.26437
Received November22, 2025
Peer reviewed: April 15, 2026
Revised: May 15, 2026
Published: June 30, 2026

EARLY BREAST CANCER DIAGNOSIS IN MAMMOGRAPHY THROUGH MICROCALCIFICATION AND MASS SEGMENTATION WITH DEEP LEARNING CLASSIFICATION

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ABSTRACT

Purpose: Breast cancer is one of the leading causes of death in women worldwide, and its early detection plays an important role in the success of treatment and increasing patient survival. Mammography is one of the main imaging methods for early detection of this disease, and the detection of microcalcifications (MCs) is of great importance in it.

Design/Methodology/Approach: However, accurate identification and classification of MCs due to their small size, different distribution pattern, appearance diversity, and similarity to normal breast tissue remains a major challenge in mammography image analysis. In this study, a method based on deep learning (DL) and recurrent neural network (RNN) is presented for the classification of MCs in mammography images. First, effective features are extracted using maximum curvature descriptors and morphological operations, and then these features are fed to the RNN to distinguish benign and malignant lesions.

Research Limitation: The proposed method was evaluated on a limited mammography dataset, and its performance may vary when applied to larger, more diverse clinical datasets acquired with different imaging devices and at different healthcare institutions. Future studies should validate the model on multi-centre datasets and investigate its generalizability in real-world clinical environments.

Findings: The results showed that the proposed method has good performance and achieved a sensitivity of 98.00%, accuracy of 97.50%, positive predictive value of 98.30% and negative predictive value of 96.32%.

Practical Implication: From a practical point of view, this method can be used to develop intelligent diagnostic assistance systems and reduce diagnostic errors by supporting radiologists' decisions.

ISSN: 2408-7920

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Social Implication: Also, from a social point of view, early diagnosis can help reduce treatment delays, lower costs, and improve patients' quality of life.
Originality/Value: This study presents a novel framework that integrates maximum-curvature descriptors, morphological operations, and a recurrent neural network (RNN) for classifying microcalcifications in mammography images.

Keywords: *Breast cancer. feature extraction. mammography. microcalcification. recurrent neural network.*

INTRODUCTION

Breast cancer is one of the most common and dangerous diseases affecting women worldwide. According to the World Health Organisation, more than 2.1 million women are diagnosed with breast cancer annually, and about 627,000 deaths from the disease were reported in 2018 (Blahová, Kostolný, & Cimrák, 2025; Abolghasemi, Emadi, & Karimi, 2024; Khosravi et al., 2024; Karimi, Harouni, & Rafieipour, 2021).

Breast cancer accounts for about 15% of cancer deaths among women and is the most common cancer and the third leading cause of death in women worldwide (Kumar et al., 2025). Among the signs visible on mammography images, microcalcifications (MCs) are among the earliest radiographic signs of malignancy. Therefore, their accurate identification can play an important role in timely intervention and early diagnosis. Unlike larger masses or abnormalities, MCs usually have a very delicate appearance, and their distribution patterns vary across images. These characteristics make their automated analysis technically challenging. Therefore, accurate identification of MCs is essential in breast cancer diagnostic systems (Vijayalakshmi, Pandey, Pandey, & Lelisho, 2025).

Early identification of breast cancer can play an essential role in raising the prospects for successful therapy and patient survival. X-ray mammography is one of the most used procedures in numerous screening approaches for detection of tumours and breast abnormalities. But sometimes it is not that easy to read the mammographic images. The diagnosis procedure in many cases is complicated by low picture quality, subtle indications, noise, and the similarity of suspicious areas to normal breast tissue (Kadhim, Sadeghi, Abdalrada, Arandian, & Khorsand, 2025; Leong, Hasikin, Lai, Mohd Zain, & Azizan, 2022; Khoshnoudi, Sadeghi, & Faghani, 2019) .

One of the important signs of early breast cancer is the observation of MCs on mammographic images. These very small calcium deposits usually appear as tiny white dots on the image. Their accurate identification is of great importance for early diagnosis of the disease; However, their very small size, irregular distribution, and in some cases their similarity to natural tissues make this process challenging (Garmaserh & Emadi, 2025; Khalili & Emadi, 2025; Qureshi et al., 2024; Asgarnezhad et al., 2023).

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Although most MCs are benign, some patterns can be indicative of malignancy; for example, clustered deposits or irregularly shaped deposits are more diagnostically significant (Yang, Khosravi, Walt, Krishnan, & Sarkar, 2025). On the other hand, the likelihood of observing such patterns increases with age. Therefore, the existence of accurate and reliable diagnostic systems is of greater importance, especially for the elderly population (Harouni et al., 2021).

In this regard, in recent years, image processing and machine learning methods have been considered as promising tools for automatic analysis of mammography images. These systems usually involve several main steps, including preprocessing, segmentation, feature extraction, and classification, each of which can improve diagnostic accuracy and assist radiologists in decision-making (Aliabadi et al., 2025; Khosravi et al., 2025).

In this study, a new DL-based method for the automatic classification of MCs in mammography images is proposed, using an RNN (Sum, 2022). First, the maximum curvature descriptor is used to identify the regions of interest, and then morphological operators are used to refine the boundaries of these regions (Al-shareeda et al., 2026; Alaidany & Mahdi, 2025; Faleh et al., 2025; Gunaware, 2025; Ordóñez et al., 2025; Stergiou et al., 2023). Next, distinguishing features from the regions of interest are extracted and fed into an RNN for classification into benign and malignant groups. The RNN's feedback mechanism enables it to learn complex patterns and sequential dependencies, thereby modelling fine image structures more accurately (Luo et al., 2024).

Although various studies have addressed the problem of breast tumour detection, many of them still face limitations such as random location of lesions, differences in their shape and size, as well as inherent limitations in the quality of mammographic images (Ali et al., 2025; Çakmak & Pacal, 2025; Çakmak & Zeynalov, 2025; Karimi et al., 2025). The main contribution of this research is the development of a multi-stage decision-making framework that simultaneously utilises spatial texture features and edge morphology to improve classification performance. In this method, integrating feature selection for dimensionality reduction and employing a suitable RNN architecture increases detection accuracy while maintaining computational efficiency. This hybrid system can provide a robust and scalable solution for the early detection of breast cancer using mammographic images.

The innovation of this study lies in the design of a hybrid, multi-stage framework for the early detection of breast cancer in mammographic images. Unlike many previous studies that rely only on convolutional neural networks (CNN) or traditional classifiers such as support vector machines (SVM) and K-nearest neighbor (KNN), the proposed method in this study has two main innovations. First, maximum curvature descriptors, which are used for the first time in mammography in this study, are used to extract fine structures of MCs. This process is complemented by morphological operators; operators that refine the regions of interest and reduce irrelevant noise, thereby increasing the discriminability of features. Second, an RNN is used in the classification stage so that the model can take into account both spatial and ordinal dependencies present in the extracted features. The combination of novel feature extraction and

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RNN-based classification provides a robust and technically distinct framework that outperforms existing methods.

The experimental results show that the proposed multi-step process has significantly improved the accuracy, sensitivity, and precision of diagnosis. Therefore, the proposed framework, in addition to combining multiple methods, can serve as a practical and scalable solution for cancer diagnosis from medical images.

The rest of the paper is organised as follows: In the second section, the research background and fundamentals related to breast cancer diagnosis using mammography are reviewed. In the third section, the proposed method is explained, which includes the steps of image preprocessing, feature extraction, and RNN-based classifier design. The fourth section presents and analyses the experimental results and compares the performance of the proposed method with existing methods. Finally, in the fifth section, the research summary is presented, and the most important findings and suggestions for further research are stated.

RELATED WORK

In recent years, the use of intelligent algorithms in the diagnosis and classification of medical diseases, especially cancer, has attracted the attention of many researchers (Alaidany et al., 2026; Zhang et al., 2024; Alaidany et al. 2022). Accurate classification of tumours is an important part of medical diagnosis, and software methods have played an effective role in this field (Khosravi et al., 2024). However, the analysis and classification of medical images remain challenging because these images are complex in their data structure, and their quality varies across different imaging conditions. Among various computational methods, machine learning, and especially DL, have gained prominence due to their ability to learn hierarchical features and extract complex patterns from large datasets. Several studies have investigated the application of image processing and machine learning in breast cancer classification using mammography images.

In one of these studies, a three-stage system was presented, including image preprocessing, feature extraction, and classification. In this method, textural and geometric features were extracted from the images, and a perceptron-based neural network (ANN) was then used to classify the 24 features into two groups: benign and malignant. The results of this study showed an average level of accuracy (Patil & Biradar, 2021).

In another approach, dimensionality reduction of mammography data was considered to increase processing speed and improve classification accuracy. This method was tested on a public dataset and achieved relatively good classification performance (Priyadarshni et al., 2024).

In another study, a hybrid model based on the TNM staging system and ant colony optimisation algorithm was used to diagnose the clinical stage of breast cancer. This system was evaluated using national and local data, and its results varied by data source and model complexity

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(Veeranjaneyulu et al., 2025). Also, a method based on histogram analysis, wavelet transform, genetic algorithm, and morphological operations was presented for image segmentation and classification. This hybrid approach achieved high accuracy in distinguishing benign from malignant tumours in mammography images (Ajlouni et al., 2024). In another study, segmentation based on area growth and statistical and spatial features was followed by fuzzy thresholding based on entropy. Despite extracting a large set of features, the final classification accuracy of this method remained at an average level (Yazid et al., 2022).

A probabilistic model based on nonparametric kernel density estimation was also implemented for breast cancer classification on two benchmark datasets. Among the kernel functions examined, the Gaussian kernel with Euclidean distance achieved the best accuracy (Guo et al., 2023). In another approach, a pixel-based method was introduced in which the directional similarity between the central pixel and neighbouring pixels was used to identify the needle-shaped structures of the tumour. These features improved segmentation accuracy and yielded good classification results (Win et al., 2025). Also, a method that includes morphological operations, a 2D wavelet transform, and Laplacian and gradient filters was proposed to reduce image noise and improve mass detection. This method was useful for detecting masses and MCs (Das & Mohanty, 2025).

In another study, a hybrid algorithm based on symmetry-based anatomical analysis was designed to detect a tumour by comparing pixel densities on both sides of the breast. Despite its simplicity, this method showed acceptable performance when its structural assumptions were met (Dey, Ali, & Rajan, 2023). In addition, a model based on a rich set of features was presented, combining histogram analysis, morphological operators, and dimensionality reduction. The aim of this model was to improve lesion boundary detection and enhance the performance of classifiers, for example, SVM and ANN (Neha, Chaturvedi, & Shafique, 2024).

The most recent breakthrough in this field is the recently proposed InceptionNeXt-Transformer model. This model is an effort to combine the power of visual transformers to perceive broader picture relationships with the strength of convolutional neural networks for retrieving multiscale information. This leads to better treatment of breast cancer images by considering the finer features of individual regions and their overall connectivity. The hybrid architecture is evaluated on several datasets, including ultrasound, histopathological, and mammography images from MIAS, INbreast, and DDSM. Computational efficiency, very robust performance and near-perfect accuracy have been established (Pacal & Attallah, 2025). These advancements notwithstanding, much research still demonstrates important limits.

The performance of diagnostic methods depends on a number of factors, such as the quality of the dataset, image noise, and the algorithm's sensitivity to parameter choices. This is particularly true for morphological operations-based methods. This highlights the ongoing need for more flexible and resilient systems that deliver consistent, reliable performance across a range of imaging conditions with minimal human operator interaction. In recent years, intelligent algorithms have been used for disease classification and diagnosis, especially in cancer research. Breast cancer detection from mammographic images using image processing

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and machine learning has also been studied in many studies. These studies commonly use preprocessing, feature extraction and classification to improve the precision of mass and MC identification.

In some studies, textural and geometric features have been used together with classifiers such as artificial neural networks and optimisation algorithms (Ghahfarrokhi et al., 2023). Others have used principal component analysis, morphological operations, nonparametric density estimation, and mixed models to better distinguish benign and malignant lesions. Although some of these methods have shown promising results, their performance often depends on image quality, noise level, and how the algorithm parameters are set. For this reason, there is still a need for methods that, while maintaining high accuracy, are more robust to changes in imaging conditions and are less dependent on manual adjustments.

Despite the progress made, three main limitations remain in existing research. First, many studies still rely on hand-crafted features or traditional classifiers, which usually lack sufficient power to capture complex spatial and ordinal dependencies in mammography data. Second, methods based on morphological or tissue features are often sensitive to noise, image quality, and parameter selection, which limits their applicability in real-world clinical settings. Third, although convolutional neural networks have been widely used, their main focus is on spatial features, and the ordinal relationships between extracted patterns are less considered. This gap indicates the need for a hybrid framework that, in addition to accurate feature extraction, uses recursive architectures to model ordinal dependencies, thereby enabling MC classification with greater reliability and generalizability.

METHODOLOGY

The primary purpose of this research is the diagnosis of breast cancer through the detection of calcium microcalcifications in mammographic pictures. For this goal, morphological operations and the maximum curvature technique are initially employed, and the final classification is then performed using a deep learning model based on recurrent neural networks.

In this method, mammographic images are first pre-processed to improve image quality and minimise existing noise. After image improvement, morphological and curvature-based features are recovered from the locations where MCs are more likely to be present. These features provide information about texture, shape and edge details and are employed in the classification stage. The suggested method starts with image segmentation to extract the regions of interest, as illustrated in Figure 1. Then, the appropriate features are extracted from these locations.

The dataset is split into two parts: 70% is used to train the RNN, and the remaining 30% is used to assess model performance. Due to its feedback structure, the RNN model can learn both spatial and sequential patterns and thus identify benign and malignant discoveries with high accuracy. The suggested hybrid system is generalised to facilitate earlier and more accurate

ISSN: 2408-7920

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breast cancer diagnosis by exploiting image enhancement, structural feature analysis, and deep learning. The different steps of the suggested method are clearly discussed in the following section.

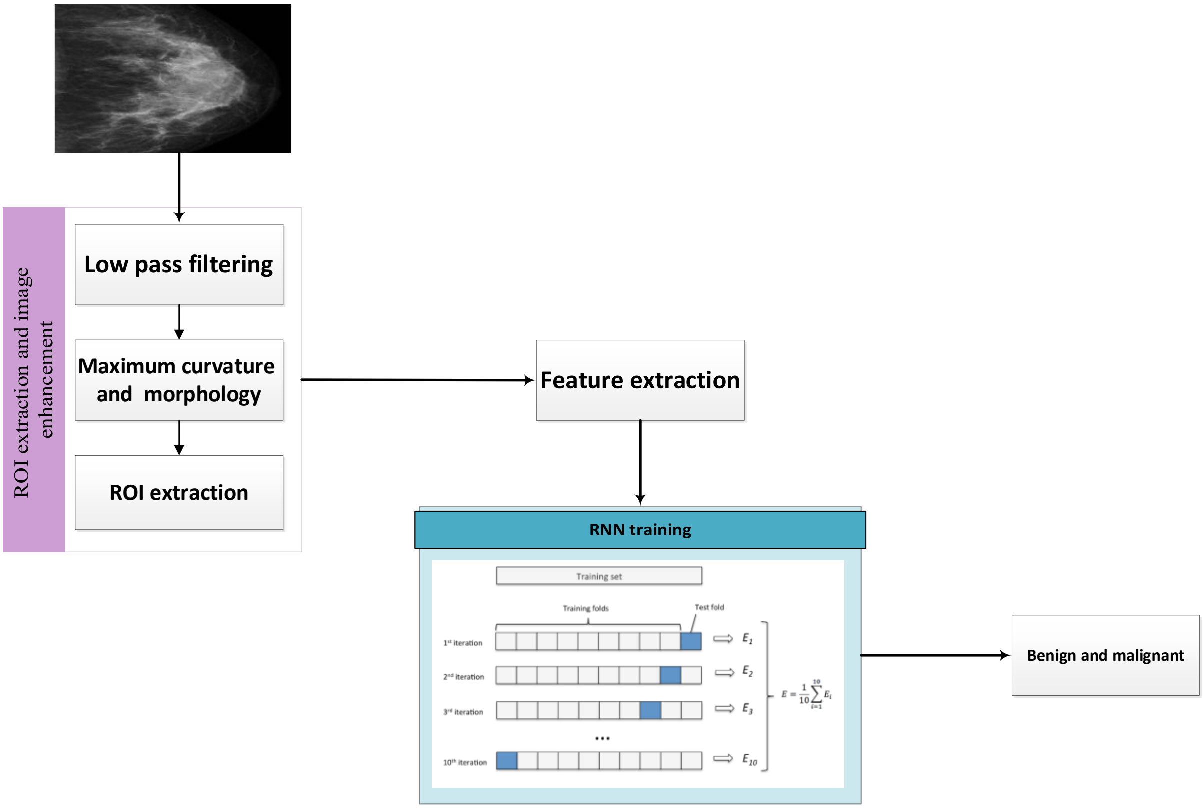

Figure 1: Proposed method diagram

Preprocessing

Preprocessing is an important step before feature extraction and analysis of mammographic pictures. These images generally lack sufficient contrast and resolution due to limitations of the imaging instrument. It is difficult to differentiate among breast tissues, such as fat, milk ducts, and lymph nodes. This problem is further enhanced when MCs are also present in the image, as these areas are quite small and are frequently visible, scattered across the image. To overcome these challenges, some image enhancement procedures were conducted.

In the first phase, image normalisation was used to make the brightness levels across samples as uniform as possible and to reduce the effects of differences due to imaging conditions. Then, to make the delicate patterns of MCs more apparent, histogram equalisation was utilised to enhance the image's local contrast. Subsequently, filtering procedures were performed to decrease noise and irrelevant background artefacts and to make diagnostically significant structures more clearly visible. Specifically, a low-pass averaging filter was initially employed

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to minimise high-frequency noise, followed by a local Laplacian filter to emphasise edges and boost contrast. Figure 2a shows the original image and Figure 2b shows the improved image.

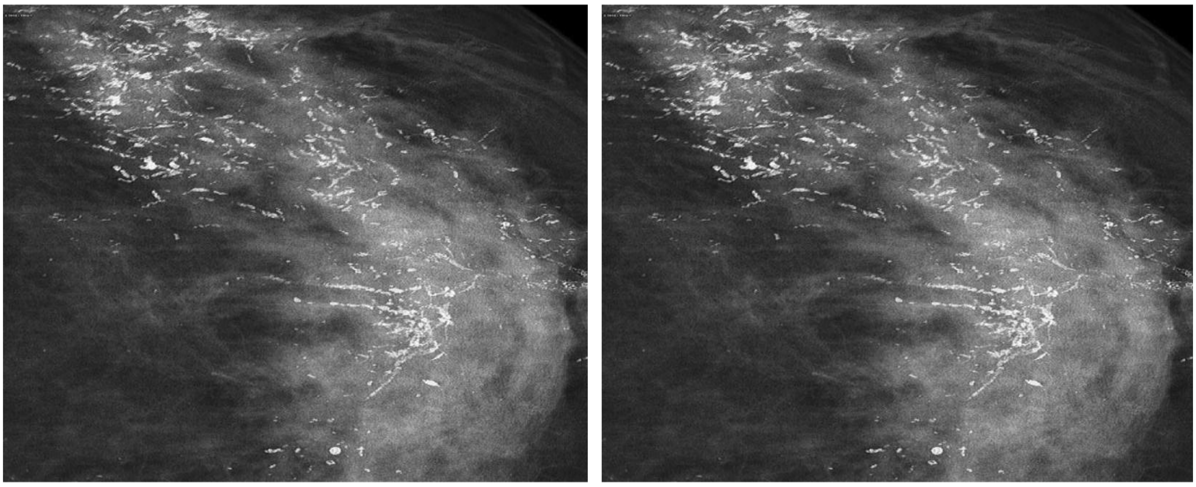
a b

Figure 2: a) Original image, b)Enhanced image after pre-processing

Maximum curvature

In this study, the maximum curvature algorithm was used to extract features and more accurately detect edges associated with MCs in mammography images. The importance of this method stems from the fact that calcium particles are usually very small, and their boundaries cannot be easily distinguished from those of the surrounding tissue. Therefore, a method is needed that can better reveal subtle changes in brightness intensity in the image.

In this algorithm, the image's brightness profile is first examined at different angles to identify potential edge regions. However, brightness alone cannot accurately determine the centre of the edge. For this reason, the curvature is calculated from the second derivative of the brightness profile.

In the curvature graph, points that are more concave are usually more likely to be located on the edge. To improve selection accuracy, each point is scored based on its curvature and the extent of the surrounding area. Then, points whose scores are higher than a specified threshold are selected as the centre of the edge. This process enables more consistent identification of fine, fuzzy edges, resulting in more accurate detection of MCs in mammography images. Then, points whose scores are higher than a specified threshold are selected as the centre of the edge. This process allows for more consistent detection of fine, indistinct edges. As a result, the maximum curvature algorithm can help detect MCs more effectively, which is important for early breast cancer detection.

This algorithm is the main part of the feature extraction stage. The whole process of maximum curvature is divided into three steps: extracting the centre positions along the edges, increasing sensitivity, and connecting the centre points during edge enhancement. In order to extract the

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central positions of the edges, first the cross-sectional profile analysis is applied on the image, and then the local maxima in the cross-sectional profile are calculated. To further explain this method, if the$F(x, y)$brightness intensity value of the pixel (x, y)then $P_f(z)$ it is a cross-sectional profile obtained from$F(x, y)$

As seen in Figure 3, this algorithm is convoluted as a line on the image at different angles. Then, based on the image's brightness, a graph is drawn for each column of pixels. In the resulting diagram, convex points are usually recognised as edges. But this diagram is not accurate enough to determine the centre points of the edge in the image. For this purpose, the maximum curvature values are calculated using the cross-sectional profile values. This conversion is calculated using equation 1.

$$k(z) = \frac{\frac{d^2 p_f(z)}{dz^2}}{\left(1 + \left(\frac{dp_f(z)}{dz}\right)^2\right)^{\frac{3}{2}}} \tag{1}$$

In the above relation $P_f(z)$, a cross-sectional surface profile, dz is the derivative operator, and k(z) is the maximum value of curvature. After this transformation, the obtained graph is recognised in the concave points with a very high probability of the edges inside the image. Figure 3 shows an example of the profile diagram of the cross-sectional area and maximum curvatures.

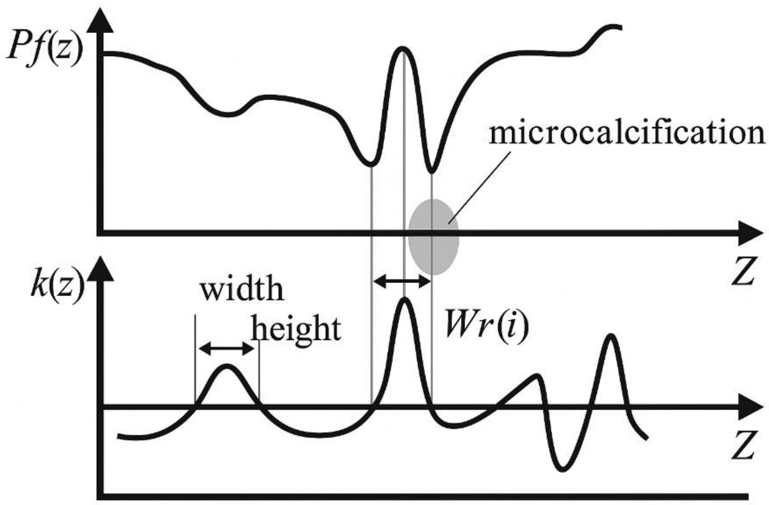

Figure 3: An example of a graph of cross-sectional profile and maximum curvature (Tan et al., 2017)

In Figure 3, by converting the maximum curves, the edge points are roughly identified, but again, there is no necessary accuracy in identifying the edge. To overcome this challenge, a weighting system for the concave points of maximum curvature is assigned to each of the points

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in some way a probability of being in the edge points. This weighting system is calculated with the following relationship.

$$S_{cr}(z_i') = k(z_i')W_r(i) \tag{2}$$

In the weighting system in relation 2, i is one of the maximum points of the maximum curvature diagram and $W_r(i)$ is equal to the product of the width of the concave area by the value of z_i'. The score value of each z_i' is equal to the product of the described weight and the maximum curvature value calculated for that point, and Figure 3 is an example of the results of the weighting system.

In addition to the maximum curvature algorithm's ability to highlight boundary information, this method also exhibits good stability under brightness changes and low-contrast conditions, which are frequently seen in mammography images. This feature makes MCs more visible even in dense breast tissues, because the algorithm highlights areas where brightness changes are more noticeable. On the other hand, the curvature-based representation can preserve fine structural details while reducing noise and irrelevant background parts. This is of great importance for detecting small and irregular calcifications. Therefore, maximum curvature can serve as a suitable and reliable feature for extracting regions of interest and performing classification in subsequent stages.

Morphological Operators

In the post-processing stage, to identify MCs more accurately, morphological operations are applied to the image obtained from the maximum curvature analysis. The use of morphological operators [2] helps better identify areas with greater pixel connectivity and makes the parts where the probability of MCs is higher more visible than the rest of the image. In this stage, the erosion operator is used to remove areas with a low probability of MCs. Some of these areas may have been mistakenly identified as suspicious in the previous stages due to experimental thresholds. The erosion performance depends on the size and shape of the structural element; therefore, several types of structural elements were investigated. Finally, the cubic structural element yielded the best result because it was more compatible with MCs in terms of size and appearance.

$$Img_{mic} = Img_{fuzzy} \ominus \mathrm{B} \tag{3}$$

ISSN: 2408-7920

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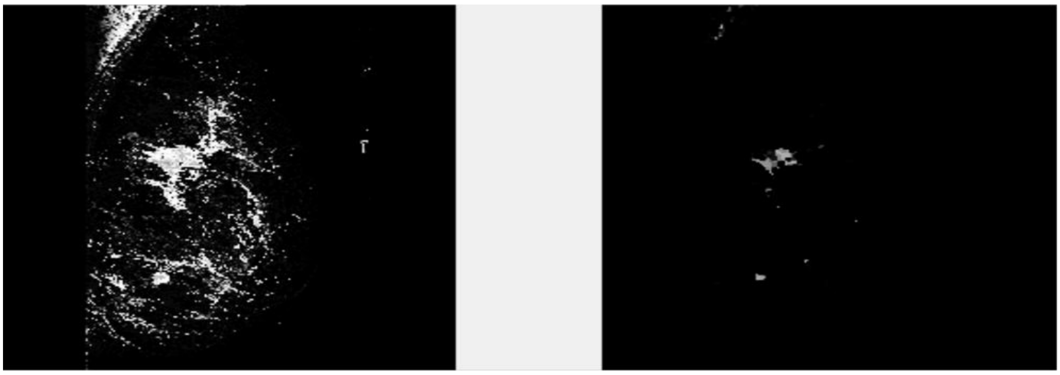

a b

Figure 4: a) Before, b) Extracted region for feature extraction

In the ROI extraction stage, the goal is to separate the areas associated with MCs from the background and other unrelated breast tissues. To do this, the images were first preprocessed using low-pass and Laplacian filters to reduce noise and better define the boundaries of suspicious areas. Then, morphological operations, such as erosion and reconstruction, were applied to remove small and irrelevant structures while preserving important image patterns. Next, potential microcalcification areas were extracted based on geometric features and brightness levels. This process allows for more accurate selection of areas of interest, and only areas associated with MCs are entered into the ANN. As a result, the effects of noise and additional background information in subsequent analysis stages are reduced.

Classification

RNNs are a class of DL models that can learn sequential dependencies through their feedback connections. In this structure, the output information can be fed back into the hidden layers, helping the network retain information from previous stages. For this reason, RNNs are very useful for identifying patterns in data with some form of internal order or dependence.

In these networks, each hidden neuron is connected to a feedback neuron, ensuring that the network's previous state remains part of the learning process. In terms of structure, an RNN consists of an input layer, a hidden layer, an output layer, and a feedback layer, with data flowing through the network via nonlinear weighting functions. Due to their flexibility, fast convergence, and ability to model complex patterns, these networks have been successfully used in various fields, including medical image analysis.

Figure 5 shows the multi-input RNN model, where the number of neurons in the input and hidden layers are m and n, respectively, and a single neuron is used in the output layer. If $x_{it} = \{i = 1,2,\dots,m\}$is the input vector set of neurons at time t and y_{t+1} represents the output of the network at the moment t+1, a nd also $z_{jt} = \{j = 1,2,\dots,n\}$ is the number of hidden-layer neurons at time t and $u_{jt} = \{j = 1,2,\dots,n\}$ is the number of hidden-layer neurons. w_{ij} be the weight of the connections between the i-th neuron, or the i-th neuron in the input layer and the

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j-th neuron in the hidden layer. V_j and C_j are the weights of connections of neuron j to the neuron of the hidden layer in the return and output layers. The hidden layer mode will be as follows: The inputs to all neurons in the hidden layer will be calculated using equation (4).

$$net_{jt}(k) = \sum_{i=1}^{n} w_{ij} x_{ij}(k-1) + \sum_{j=1}^{m} c_j u_{jt}(k), \tag{4}$$
$$u_{jt}(k) = z_{jt}(k-1), i = 1,2, \ldots, n. \quad j = 1,2, \ldots, m.$$

And the outputs of the hidden neurons are calculated in the style of equation5.

$$z_{jt}(k) = f_H\left(net_{jt}(k)\right) = f_H\,(\sum_{i=1}^{n} w_{ij} x_{ij}(k) + \sum_{j=1}^{m} c_j u_{jt}(k)\ ) \tag{5}$$

In which the sigmoid function is considered as the activation function of the hidden layer. That means:

$$f_H(x) = \frac{1}{1+e^{-x}} \tag{6}$$

And the output of the hidden layer will be calculated as equation (7).

$$y_{t+1}(k) = f_H(\sum_{j=1}^{m} v_j z_{jt}(k)) \tag{7}$$

which is the introduction map in the activity function [5].

RESULTS AND DISCUSSION

To achieve a more comprehensive evaluation and enhance the model's generalizability, this study employed not only the Mammographic Image Analysis Society (MIAS) dataset but also two widely used benchmark datasets: the Curated Breast Imaging Subset of DDSM (CBIS-DDSM) and INbreast. The characteristics of these three datasets are summarised in Table 1. The MIAS dataset consists of 322 digitised mammographic images obtained from scanned films. Although this dataset is not very large in terms of the number of images, it is still used in many early studies related to breast cancer diagnosis due to its ease of access and labelling information. In contrast, the CBIS-DDSM dataset is a refined and more systematic version of the DDSM dataset and contains more than 3,000 cases, including about 10,000 images.

In this dataset, areas of masses and MCs are identified in detail, and the results are confirmed with pathology information. For this reason, CBIS-DDSM can be considered one of the largest and most reliable datasets in mammography. The INbreast dataset is also based on full-field digital mammography. This dataset is smaller in terms of the number of images, consisting of 410 images from 115 patients, but its image quality is very high, providing the researcher with greater detail in terms of resolution and bit depth. Also, the labelling of different breast lesions in this dataset is highly accurate. Using these three datasets simultaneously enables the proposed model to be evaluated not only on a single image type or specific condition, but also against data with different quality, structure, and populations.

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Table 1: Description of the databases

Dataset	Imaging Modality	Number of Images	Annotation Types	Resolution / Format
MIAS	Digitised mammography (film scanned)	322 images (207 normal, 115 abnormal: 65 benign, 50 malignant)	Masses, MCs, background tissue	1024×1024 pixels (8-bit grayscale)
CBIS-DDSM	Digitised film mammography	3,100 cases (10,000 images)	ROI-level annotations: calcifications, masses, pathology-confirmed labels	Variable (typically 1712×2736 pixels, LJPEG/DICOM)
INbreast	Full-field Digital Mammography (FFDM)	410 images (from 115 patients)	Very detailed annotations: masses, MCs, asymmetries, distortions	High-resolution DICOM (up to 4084×3328 pixels, 14-bit grayscale)

For the classification task, a 10-fold cross-validation strategy was employed, in which the dataset was randomly divided into 10 equal subsets; in each iteration, nine subsets were used for training, and one subset was used for testing, and the final performance metrics were reported as the average across all folds. In the proposed feature extraction method, the desired area is first extracted. The final step in a breast tumour zoning system is to calculate accuracy and sensitivity. Necessary explanations regarding some values used in equations 8-11 are provided.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FPP+FN} \tag{8}$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \tag{9}$$

$$\text{Precision} = \frac{TP}{TP+FP} \tag{10}$$

$$Specificity = \frac{TN}{TN+FP} \tag{11}$$

The performance of the fine-grained classification test is assessed using four key metrics: True Positive (TP) refers to the cases correctly detected as fine-grained; False Positive (FP) represents cases incorrectly identified as fine-grained; True Negative (TN) includes cases correctly identified as non-fine-grained; and False Negative (FN) refers to cases misclassified as non-fine-grained when they should have been identified as fine-grained.

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http://www.ajaronline.com
https://doi.org/10.26437
Received November22, 2025
Peer reviewed: April 15, 2026
Revised: May 15, 2026
Published: June 30, 2026

Setting Parameter

The simulations in this research were conducted on an Intel Core™ i5 CPU (7 cores, 2.60 GHz) system running Windows 10 with 8 GB of RAM. The proposed RNN was trained with the Adam optimiser (learning rate 0.001) using a batch size of 32 for up to 100 epochs with early stopping. The architecture had two hidden recurrent layers (15 neurons each, sigmoid activation) and a softmax output layer. Regularisation was achieved through dropout (0.3) and L2 weight decay (1e-4). Weights were initialised with Xavier initialisation, and training was guided by binary cross-entropy loss. Table 2 shows these details.

Table 2: Hyperparameters of the proposed RNN model

Parameter	Value/Method
Optimizer	Adam
Learning rate	0.001 (step decay, factor 0.1/20 epochs)
Batch size	32
Epochs	100 (with early stopping, patience = 10)
Hidden layers	2 recurrent layers, 15 neurons each
Activation (hidden layers)	Sigmoid
Activation (output layer)	Softmax
Regularization	Dropout = 0.3, L2 = 1e-4
Weight initialization	Xavier initialization
Loss function	Binary cross-entropy

Segmentation Results

For MC segmentation, the evaluation was performed using Precision, Sensitivity, and the Dice similarity coefficient. The Dice coefficient was calculated according to Equation (12)

$$Dice = \frac{2 * (TP)}{2 * (TP) + FN + FP} * 100 \qquad (12)$$

The results of this evaluation are presented in Table 3. As can be observed, the proposed method demonstrates satisfactory performance across all three datasets in terms of Precision, Sensitivity, and Dice. These findings indicate that the proposed model accurately detects and segments microcalcification regions in mammographic images and further confirm its generalizability across different imaging conditions.

Table 3: Evaluation of fine-grain identification in the proposed method

Dataset	Dice (%)	Sensitivity (%)	Precision (%)
MIAS	94.33	97.20	96.79
CBIS-DDSM	93.0	95.2	92.1
INbreast	89.0	91.5	90.2

Classification Results

As shown in Figure 5, the performance of the proposed RNN model on the MIAS dataset improved across all evaluation indices as the number of hidden neurons increased. This result indicates that increasing network capacity helped the model learn more complex patterns from

ISSN: 2408-7920

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http://www.ajaronline.com
https://doi.org/10.26437
Received November22, 2025
Peer reviewed: April 15, 2026
Revised: May 15, 2026
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the data and, as a result, classify lesions with greater confidence. The results in Figure 6 also show a similar trend for the CBIS-DDSM dataset. Although this dataset is more complex in terms of image volume and variety than MIAS, the proposed model achieved stable performance. This indicates that the proposed method has good reliability when faced with more diverse clinical data.

Figure 7 reports the model's performance on the INbreast dataset. Here too, increasing the number of hidden neurons led to improved results. Given the higher image quality and greater structural detail in this dataset, this result shows that the proposed method is not dependent on a single data type and can perform well under different imaging conditions. Based on the experimental results, the proposed RNN model achieves the best performance on the MIAS dataset using a 15-neuron hidden layer. This is probably related to the smaller volume and lower diversity of this dataset compared to CBIS-DDSM and INbreast, because in such conditions, the network can more easily learn the main patterns associated with MCs.

In contrast, in the other two datasets, although increasing network capacity improved performance, the larger data volume, greater image diversity, and greater structural complexity made learning more difficult. Overall, these results show that the proposed architecture can provide better performance by increasing the network capacity. Also, evaluating the model across multiple datasets shows that it is necessary to assess the method's stability and generalizability under varying imaging conditions.

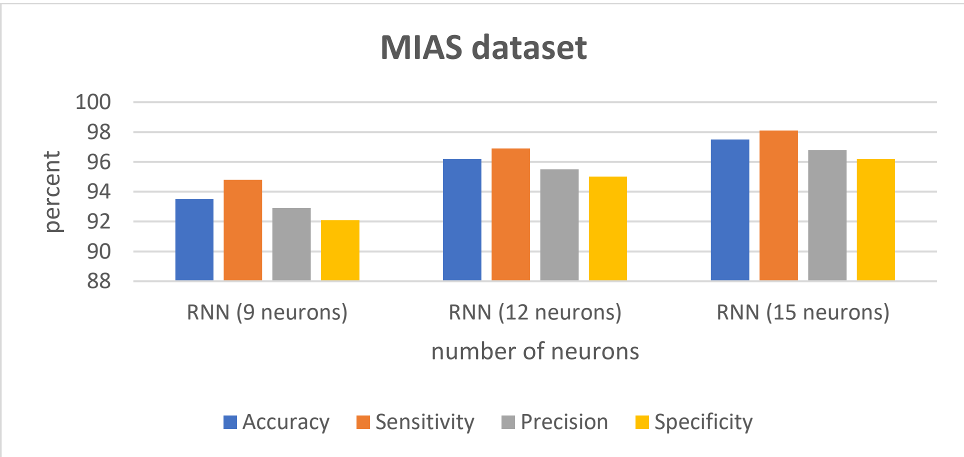

Figure 5: Performance of proposed RNN (MIAS dataset)

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http://www.ajaronline.com
https://doi.org/10.26437
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Revised: May 15, 2026
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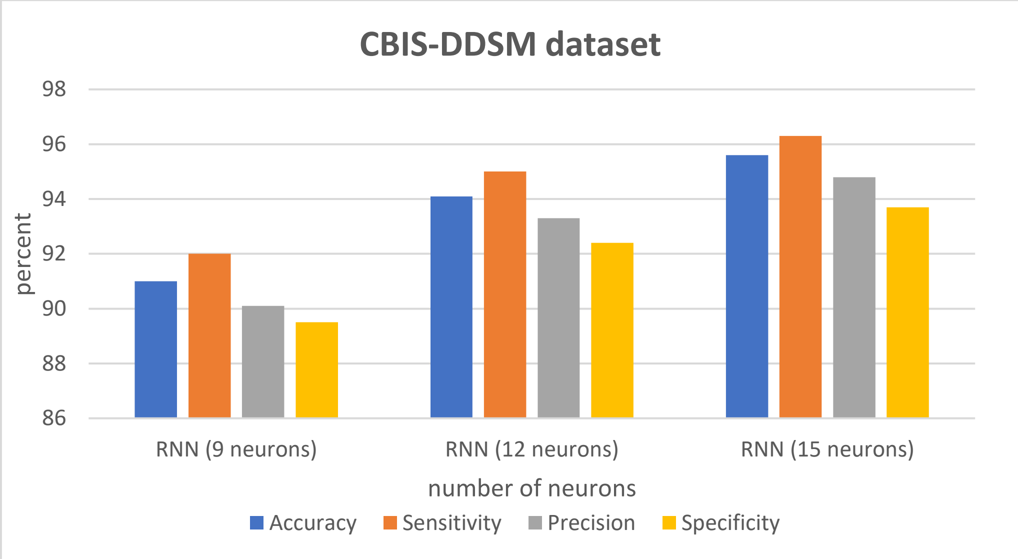

Figure 6: Performance of proposed RNN (CBIS-DDSM)

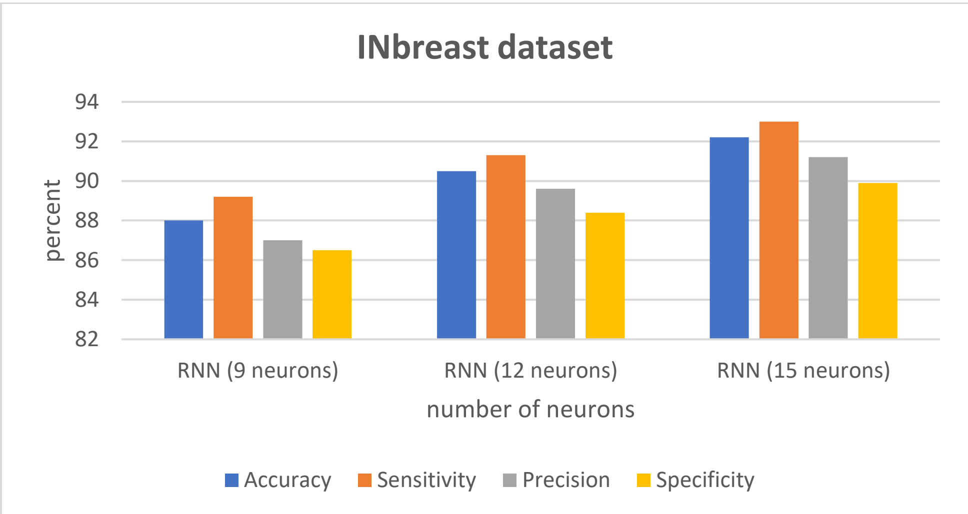

Figure 7: Performance of proposed RNN (INbreast)

Comparison with other Classifiers

The main objective of this research is to present a novel method for breast cancer diagnosis based on calcium particle detection and ANN classification methods. The proposed method has been evaluated on the datasets used. In this process, feature extraction is performed using maximum curvature and morphological features, and then KNN (K=3) is used for classification. In addition, an ANN with a hidden layer consisting of 15 neurons and an SVM with an RBF kernel have also been used as comparative classifiers.

As shown in Table 4, the proposed RNN model with 15 hidden neurons on the MIAS dataset outperformed the baseline classifiers across all evaluation indices, including accuracy,

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https://doi.org/10.26437
Received November22, 2025
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Revised: May 15, 2026
Published: June 30, 2026

sensitivity, precision, and specificity. This superiority can be attributed to the RNN's ability to model ordinal dependencies among image features. In other words, the RNN is better able to identify subtle changes in microcalcification patterns, whereas traditional classifiers such as multilayer perceptron networks, SVMs, and k-NN are usually limited in their ability to fully represent these patterns.

A similar trend is observed in Table 5, which presents results for the CBIS-DDSM dataset. This dataset is more challenging than MIAS due to its larger size and higher image diversity. However, the proposed method achieves better values in all indices compared to the baseline classifiers. This performance improvement shows that the proposed method not only performs well on simpler data but also demonstrates good robustness to more diverse mammography data, providing acceptable generalisation.

Finally, Table 6 presents the comparative results for the INbreast dataset. Although in this dataset the higher image quality and greater complexity of the structural patterns have somewhat reduced the performance of all classifiers, the proposed RNN model still achieved the best results across all evaluation criteria. This shows that the proposed method can adapt to datasets of varying complexity and effectively extract and model important features relevant to clinical diagnosis.

Table 4: Proposed method Comparison with other classifiers (MIAS)

Classifier	Accuracy	Sensitivity	Precision	Specificity
Proposed RNN (15 neurons)	97.5	98.1	96.8	96.2
MLP	93.4	94.2	92.7	91.5
SVM	92.1	92.8	91.2	90.4
KNN	90.8	91.5	90.0	89.1

Table 5: Proposed method with other classifiers (CBIS-DDSM)

Classifier	Accuracy	Sensitivity	Precision	Specificity
Proposed RNN (15 neurons)	95.6	96.3	94.8	93.7
MLP	92.0	92.9	91.4	90.6
SVM	91.3	92.1	90.2	89.8
KNN	89.7	90.5	89.0	88.2

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http://www.ajaronline.com
https://doi.org/10.26437
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Table 6: Proposed method Comparison with other (INbreast)

Classifier	Accuracy	Sensitivity	Precision	Specificity
Proposed RNN (15 neurons)	92.2	93.0	91.2	89.9
MLP	89.1	90.0	88.4	87.3
SVM	88.5	89.4	87.6	86.8
KNN	86.9	87.8	86.0	85.2

Statistical test

In Figure 8, the performance of the four classifiers on three benchmark datasets, namely MIAS, CBIS-DDSM, and INbreast, is compared simultaneously using four main indicators: accuracy, sensitivity, precision, and specificity. As shown in this heatmap, the proposed RNN model with 15 neurons outperforms the baseline classifiers, including MLP, SVM, and KNN, across all datasets and evaluation metrics. This superiority is especially noticeable on the CBIS-DDSM dataset, which is more challenging in terms of image volume and diversity, and on the INbreast dataset, which has higher-resolution images. Such a result indicates that the proposed model has stable performance under different imaging conditions and is not dependent on a specific data type. Also, the colour changes in the heat map clearly show the performance difference between the methods and indicate that the proposed method has a significant improvement over the comparative classifiers. Overall, these results confirm, both numerically and visually, that the proposed model effectively identifies subtle patterns of MCs and can classify lesions with greater reliability.

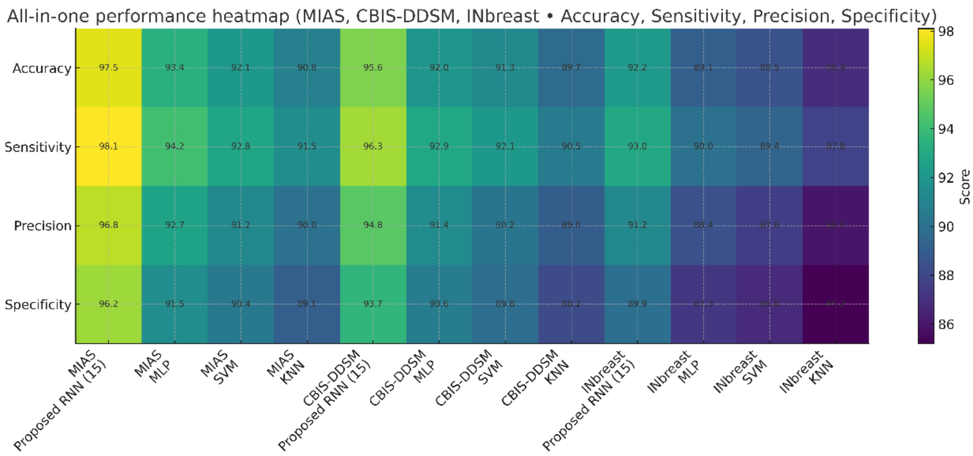

Figure 8: Statistical test in MIAS, CBIS-DDSM, and INbreast between MLP, SVM, and KNN and the proposed method

ISSN: 2408-7920

African Journal of Applied Research
Vol. 12, No. 4 (2026), pp.413-437
http://www.ajaronline.com
https://doi.org/10.26437
Received November22, 2025
Peer reviewed: April 15, 2026
Revised: May 15, 2026
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Comparison with other papers

Figure 9 compares the proposed method with the baseline paper by Omadui, Dang, and Pomplon (2021) on the MIAS dataset. The results of this comparison show that the proposed method outperforms the baseline method across all evaluation criteria: overall accuracy, sensitivity, precision, and specificity. This improvement seems to be mainly due to more accurate identification of regions of interest and the use of features that better reflect subtle differences in MC patterns. In this regard, the proposed model was able to detect small, and sometimes poorly defined, changes in microcalcifications more effectively. Replication of this improvement on several different criteria also shows that this method can be a reliable and practical approach for early detection of breast cancer.

Figure 10 also presents the results for the CBIS-DDSM dataset. In this dataset, the proposed method again outperforms the baseline paper in all evaluation criteria, including overall accuracy, sensitivity, precision, and specificity. This difference is particularly evident in sensitivity and accuracy: the model identifies MCs more accurately while reducing false positives. This result can be attributed to the combination of maximum curvature descriptors with recurrent neural networks, which results in better feature representation and more robust classification on the large and diverse CBIS-DDSM dataset (Li et al., 2017).

Figure 11 shows the comparative results for the INbreast dataset (Zamir et al., 2021). Consistent with the results obtained in CBIS-DDSM, the proposed method outperforms the baseline paper across all four evaluation indices. The greatest improvement is observed in the feature index, indicating fewer false positives and a more reliable distinction between benign and malignant cases. Given the higher image quality and greater structural complexity of the INbreast dataset, this result indicates that the proposed method is well-suited to more accurate and complex mammography data.

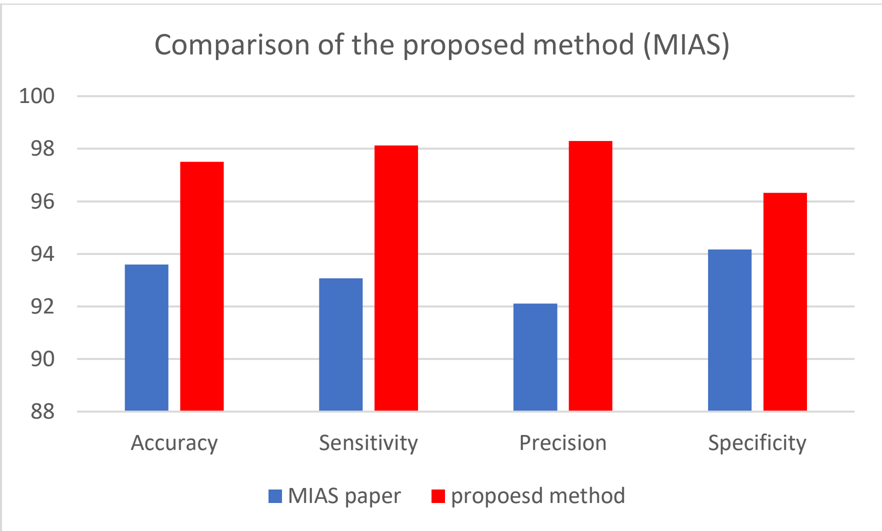

Figure 9: Comparison of the proposed method in MIAS)

ISSN: 2408-7920

African Journal of Applied Research
Vol. 12, No. 4 (2026), pp.413-437
http://www.ajaronline.com
https://doi.org/10.26437
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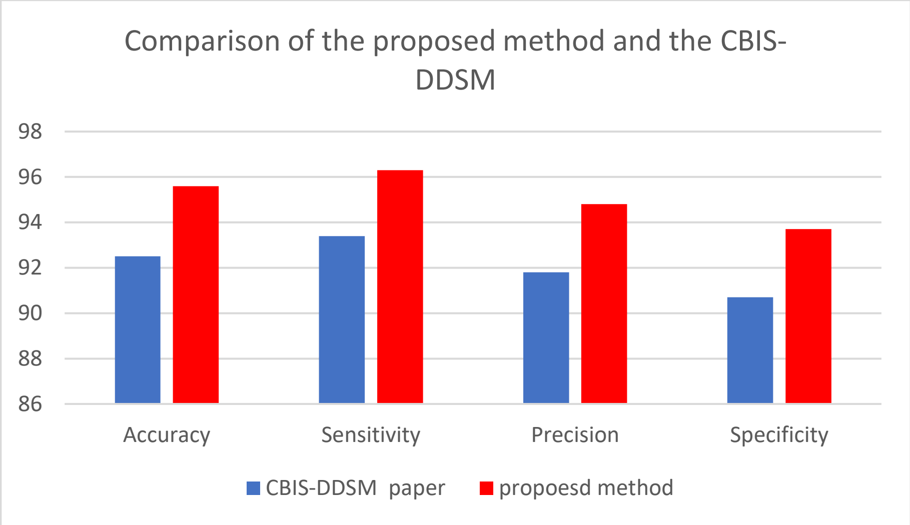

Figure 10: Comparison of the proposed method and the base paper in CBIS-DDSM

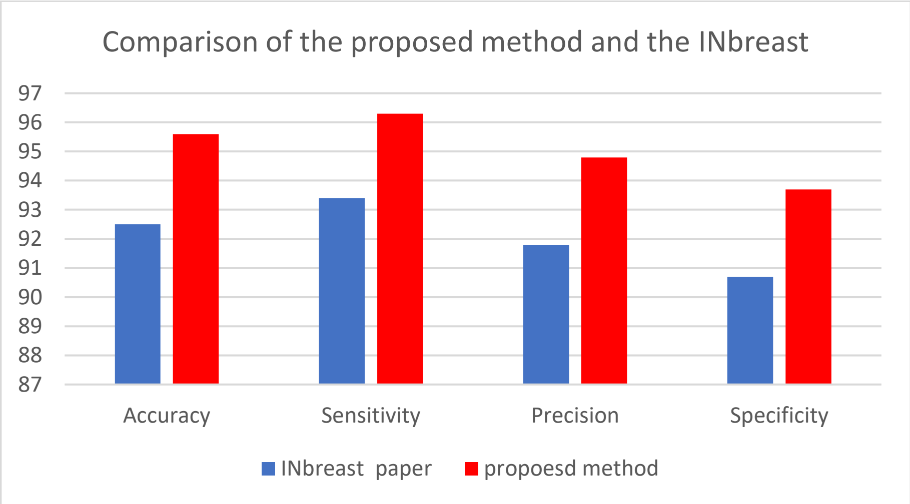

Figure 11: Comparison of the proposed method and the base paper in INbreast dataset

Discussion

The results of experiments on the three benchmark datasets MIAS, CBIS-DDSM, and INbreast show that the proposed RNN-based framework achieves stable and acceptable performance in both the segmentation and classification stages. The combination of maximum-curvature descriptors and morphological operations resulted in the extraction of the microcalcification structure with appropriate accuracy (Carpenter et al., 2022). On the other hand, the RNN was able to better model the ordinal dependencies in the extracted features. This combination made the proposed method perform better than traditional classifiers such as MLP, SVM, and KNN, as shown in Tables 4 to 6.

ISSN: 2408-7920

African Journal of Applied Research
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Received November22, 2025
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An interesting aspect of this work is that the model was assessed not on a single dataset but on three datasets with varying sizes, image quality, and imaging methods. This makes the model evaluation more realistic and enables us to speak with more confidence about its generalisability. The best numerical result was achieved on the MIAS dataset, likely due to its smaller size and lower variability. However, the proposed model also demonstrated stable and competitive performance on the CBIS-DDSM and INbreast datasets, which present more challenging conditions in terms of sample diversity, structural complexity, and imaging quality (Khourdifi et al., 2024). Therefore, it can be said that the proposed method is largely robust to imaging differences and clinical variability, which has been less seriously investigated in many previous studies. Thus, the proposed method demonstrated more stable and reliable performance than traditional machine learning methods and certain deep learning-based approaches.

A qualitative analysis of the model faults also points to salient aspects. Most of the false negatives were associated with photos in which MCs had very low contrast or overlapped with extensive glandular tissue. Under such conditions, eye identification can be difficult even for an expert. In contrast, most false positives were located in noisy areas or benign calcifications with irregular shape similar to malignant patterns. These cases suggest that the model has significant limitations with some challenging photos, yet it performed well. The results of this study are consistent with several prior studies on deep learning-based breast cancer diagnosis (Nasser & Yusof, 2023; Murtaza et al., 2020). The results suggest that the detection performance can be greatly improved by using appropriate preprocessing, accurate feature extraction and neural network classification (Musthafa et al., 2024). The combination of maximum-curvature descriptors, morphological procedures, and an RNN in this work achieved good sensitivity and accuracy. This conclusion is consistent with research highlighting the crucial contributions of feature engineering and segmentation to improving the performance of diagnostic models. However, some research has found worse outcomes due to strong image noise, limited data or more simplistic designs. Therefore, the higher performance of the suggested technique is mainly due to the multi-stage design and the utilisation of accurate structural features (Shan et al., 2024). However, to further confirm the generalisability of the model, it is necessary to analyse this strategy using larger, multicenter datasets in the future.

Overall, the results of this study indicate that the proposed framework, by combining accurate feature extraction with sequential modelling, can provide a balanced and effective solution for detecting MCs. Although it is necessary to investigate the model on larger, multicenter datasets with additional clinical information to increase its clinical applicability, the current results indicate that this method can be a suitable basis for the development of scalable diagnostic support systems that can be used in clinical settings

CONCLUSION

This paper presents a novel method for breast cancer diagnosis based on detecting calcium particles in mammography images, evaluated with an RNN. In the proposed method, after extracting morphological features and maximum curvature from the images, the features were

ISSN: 2408-7920

African Journal of Applied Research
Vol. 12, No. 4 (2026), pp.413-437
http://www.ajaronline.com
https://doi.org/10.26437
Received November22, 2025
Peer reviewed: April 15, 2026
Revised: May 15, 2026
Published: June 30, 2026

classified using an RNN. The classifier was trained with 9-, 12-, and 15-layer architectures, achieving the highest accuracy of 100% with the 15-layer configuration. For further evaluation, the extracted features were also classified using SVM, KNN, and MLP classifiers. Each classification method was implemented ten times, and the final results were recorded.

The proposed method demonstrated superior performance, achieving an accuracy of 97.50%, sensitivity of 98.30%, positive predictive value of 98.30%, and negative predictive value (recall) of 96.32%, outperforming other classification methods. Compared with other methods, the results further confirm the superiority of the proposed method. State the practical and social implications. One of the key limitations of this study is the exclusive use of the MIAS dataset for model training and evaluation. Although the use of MIAS is a good starting point due to its public availability and well-defined structure, limitations such as the small size and low diversity of the images make the model's generalizability in the real world questionable. Therefore, in future work, we intend to challenge the model's performance by integrating more comprehensive datasets such as CBIS-DDSM and INbreast, and to ensure its effectiveness across a wider range of clinical situations.

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ISSN: 2408-7920