International Journal of Natural and Engineering Sciences
E-ISSN: 2146-0086 18(3): 154-163, 2024
Research Article

A fusion of fuzzy clustering and neural networks-based diagnosis of breast cancer by mammography micro-calcification

Shima Zarrabi Baboldasht[1], Neda Behzadfar[2,]*

[1]*Department of Electrical Engineering, Najafabad Branch, Islamic Azad University, Najafabad, Iran*
[2]*Digital Processing and Machine Vision Research Center, Najafabad Branch, Islamic Azad University, Najafabad, Iran*

*Corresponding author: n.behzadfar@pel.iaun.ac.ir

(Received: May 8, 2024 / Accepted: September 15, 2024)

Abstract

Detecting micro-calcifications in mammography images is a crucial step in the early diagnosis of breast cancer, and enhancing image quality through pre-processing plays a vital role. In this research, we propose a fuzzy clustering algorithm-based approach to accurately identify micro-calcifications in mammography images. To address the low quality of mammograms, pre-processing techniques were applied to improve image clarity. A suitable membership function was defined to identify calcified regions using fuzzy clustering. The detected regions were then compared with those identified by specialists, achieving an improved identification accuracy of 96.7% and a sensitivity of 97.2%, compared to previous methods which had 95% accuracy and 90.5% sensitivity. In the next phase, neural networks were employed to classify the extracted regions into benign and malignant categories. Diagnostic performance was evaluated using identification accuracy, sensitivity, and positive and negative predictive values. The proposed method demonstrated positive results with an identification accuracy of 97.5%, sensitivity of 98.1%, positive predictive value of 98.3%, and negative predictive value of 96.3%. These outcomes indicate that the proposed fusion of fuzzy clustering and neural networks enhances diagnostic precision, owing to its high accuracy in region extraction and the distinctive features it identifies.

Keywords: breast cancer, fuzzy, mammography image, micro-calcification, neural networks

Introduction

Neural networks have become indispensable in both engineering and medical science, revolutionizing these fields with their ability to model complex patterns and deliver highly accurate predictions [1,2]. In engineering, neural networks have driven significant advancements, particularly in control systems, estimation, clustering, and predictive maintenance [3,4]. These developments have substantially enhanced productivity and sparked innovation across various industries [5,6]. In medical science, neural networks have ushered in a new era, leading to breakthroughs in diagnostics, drug discovery, and personalized treatment strategies [7,8]. By enabling healthcare professionals to analyze vast amounts of patient data, neural networks facilitate the detection of subtle patterns and correlations that might otherwise remain hidden, greatly improving the accuracy of medical assessments and treatments [9,10].

Breast cancer is characterized by the uncontrolled growth of cells, leading to the formation of tumors that are detectable through X-ray or palpation [11,12]. While the majority of breast masses are non-cancerous (benign) and pose no threat to life, they do grow abnormally. However, these benign tumors do not metastasize beyond the breast tissue [13,14]. It is worth noting that certain benign breast masses can elevate the risk of developing breast cancer in women. The outcomes and complications of breast cancer can vary significantly based on several factors, including the specific type of cancer, its clinical stage, and the age of the individual affected [15,16]. Early detection and diagnosis play a pivotal role in improving treatment outcomes and survival rates for breast cancer patients. Mammography is a crucial radiographic imaging technique used for the early detection and diagnosis of breast cancer, making it one of the most significant checkup tests for women's health [17,18]. Regular mammography screenings are recommended as a routine test for women, starting from the age of 40. The frequency of screenings may vary based on patient’s preference, individual risk factors, family history, and medical recommendations. However, for most women, undergoing mammograms every one or two years is a standard practice to ensure early detection and effective management of breast cancer [19,20]. Breast calcification, also known as mammary calcification, refers to the presence of small deposits of calcium within the breast tissue. These calcifications can appear on a mammogram as tiny white spots and can be categorized as microcalcifications or macrocalcifications, depending on their size. Microcalcifications are very small and appear as fine white specks on the mammogram. They are commonly seen in both benign and malignant breast conditions. They can sometimes indicate early stages of breast cancer and may require further evaluation, such as a biopsy, to determine their significance. Malignant microcalcifications, if left unaddressed, can lead to significant health issues over time, as they have the potential to grow and eventually develop into breast tumors. Identifying and accurately interpreting these calcifications in mammography images is critical for early detection and timely intervention in breast cancer cases. However, one of the challenges faced by radiologists is distinguishing between benign and malignant calcification in mammography images. At times, these grains may be mistaken for image noise particles, complicating the diagnostic process. The differentiation between benign and malignant calcifications requires a high level of expertise and careful analysis by the radiologist [21,22].

Indeed, extensive research has been conducted to identify breast cancer and effectively differentiate between benign and malignant microcalcifications in digital mammography images. Calcifications in mammography images can vary significantly in appearance, making their identification and classification a complex task. The shape, size, and distribution of calcifications can differ from one patient to another, and even within the same individual over time. This variability increases the difficulty of distinguishing between benign and malignant calcifications solely based on visual inspection. Breast cancer detection involves four essential steps: pre-processing, segmentation, feature extraction, and classification. Pre-processing aims to enhance mammography image quality and reduce noise. Segmentation identifies different areas of the breast, including tumors and small calcifications. Feature extraction captures relevant characteristics like texture and shape. Finally, classification models distinguish between benign and malignant abnormalities. Pre-processing plays a vital role in breast cancer detection by reducing noise, removing irrelevant information, and improving image quality. These operations are crucial as they enable more accurate segmentation and extraction of the desired region of interest (ROI) with higher quality [23,24].

Proper pre-processing ensures that the subsequent steps, such as segmentation and feature extraction, are performed on cleaner and more relevant data, ultimately enhancing the overall effectiveness of breast cancer detection methods [25]. In mammography images, 10 to 15% of the content consists of high-frequency components and various levels of noise. To enhance image quality, several methods are used, including morphological operations, discrete wavelet transform [26], two-dimensional median filter [27], histogram smoothing [28], and Gabor filter [29]. These techniques aim to reduce noise and improve the clarity of the images, facilitating more accurate analysis and diagnosis of breast abnormalities in mammography.

Classification methods in breast cancer detection can be categorized into pattern-based, appearance-based, and learning-based approaches. Pattern-based methods leverage characteristic patterns in the data for classification, while appearance-based methods focus on visual features. Learning methods encompass various machine learning algorithms. Commonly used classifiers include support vector machine (SVM), neural network, and average. In detecting microcalcification, researchers have employed convolutional neural networks, Bayesian neural networks, support vector machines, particle swarm algorithms, decision trees, and random forest decision trees. These diverse methods contribute to the advancement of accurate breast cancer detection and characterization. Neural networks have a multitude of advantages in comparison to conventional methodologies. These include their capacity to effectively represent intricate, non-linear associations within datasets, autonomously acquire pertinent characteristics from the data, and effectively manage extensive datasets and intricate problem domains. These models provide a high level of generalization to previously unseen data, exhibit adaptability and ongoing improvement through the incorporation of new information and leverage the advantages of parallel processing capabilities. Neural networks could autonomously acquire hierarchical representations of data, exhibit resilience in the face of noisy and incomplete data, and effectively integrate and process information from various sources. These characteristics render neural networks highly adaptable for a wide range of applications [30,31].

Medical research in the field of breast cancer diagnosis has been extensive, yet a definitive solution has not been reached. Despite significant advancements in imaging technologies, machine learning algorithms, and diagnostic tools, breast cancer diagnosis remains a complex and challenging task.

A new method is presented in [32] that combines multimodal microscopic imaging technology with deep learning to enable fast and intelligent diagnosis of breast cancer. The research findings indicate that this multimodal imaging technology provides substantial benefits in terms of precision, efficiency, and practicality for diagnosing breast cancer. Furthermore, when combined with deep learning algorithms, the technique demonstrates robust clinical potential and encouraging prospects for implementation. This novel amalgamation demonstrates encouraging effects in augmenting the efficiency and efficacy of breast cancer diagnosis, harboring significant promise for improved patient outcomes in clinical settings.

In [33], a 4D U-Net segmentation technique is introduced for breast cancer diagnosis, which makes use of a digital infrared thermal imaging equipment. The method entails dividing areas of interest in the digital infrared thermal images. The segmented regions are subsequently fed into a binary spiking neural network (BSNN) to classify the pathological stage of breast cancer. Typically, research in this field concentrates on the geometric and statistical characteristics of images. However, the method proposed in this study utilizes a fuzzy clustering algorithm and the extraction of appropriate statistical features to detect calcium particles in mammography images.

This research introduces the utilization of a fuzzy model to detect aberrant lesions in mammograms, with a particular focus on microcalcifications, which are often challenging to detect. Previous studies in this area have made significant advancements, but they also present several limitations. For instance, many traditional approaches rely on manual or semi-automatic methods that are time-consuming and prone to human error. Additionally, conventional image processing techniques often fail to accurately separate benign from malignant lesions, leading to lower sensitivity and higher false-positive rates [34,35].

Moreover, while some machine learning models have been employed for mammography analysis, these models often struggle with small, fine particles like microcalcifications due to their subtle nature and the varying image quality in mammograms. The classification of calcifications into benign and malignant categories is also frequently underexplored or not optimized, leading to inconsistent results in clinical settings.

Our research addresses these shortcomings through the following innovations: i) Automaticity of the method: We propose a fully automated system that reduces the need for manual intervention, enhancing the efficiency and accuracy of mammogram analysis. ii) Separation of microcalcifications into benign and malignant categories: We employ a fuzzy clustering algorithm specifically designed to improve the differentiation between benign and malignant microcalcifications, offering improved classification performance. iii) Accurate detection of fine particles with high sensitivity: The system demonstrates high sensitivity in detecting fine particles such as microcalcifications, which are often overlooked by traditional methods. By integrating neural networks, we enhance the classification process to predict the location and characteristics of early lesions with greater precision [36,37].

The following is the structure of the paper. After stating the topic, reviewing several kinds of research, and stating the importance of breast cancer diagnosis from mammography images in this part, the proposed method based on fuzzy clustering and neural networks is presented in the second part. In the third part, the proposed method has been evaluated using different criteria. Finally, the conclusion is stated in the fourth section.

Materials and Methods

Breast cancer diagnosis is often a costly and complex process, with the detection of microcalcifications in mammography images playing a pivotal role in identifying malignant cells. An accurate and efficient method for detecting and analyzing these calcifications is crucial to improving early breast cancer diagnosis.

The primary objective of this study is to detect breast cancer by identifying calcified particles in mammography images using a fuzzy clustering approach, followed by classification through a neural network. To achieve this, the mammogram images undergo pre-processing to enhance their quality. Subsequently, regions of interest (ROIs) are extracted from the enhanced images, and relevant features are extracted from these ROIs for classification. This process ultimately distinguishes between benign and malignant cases. The overall workflow of the proposed method is depicted in Figure 1.

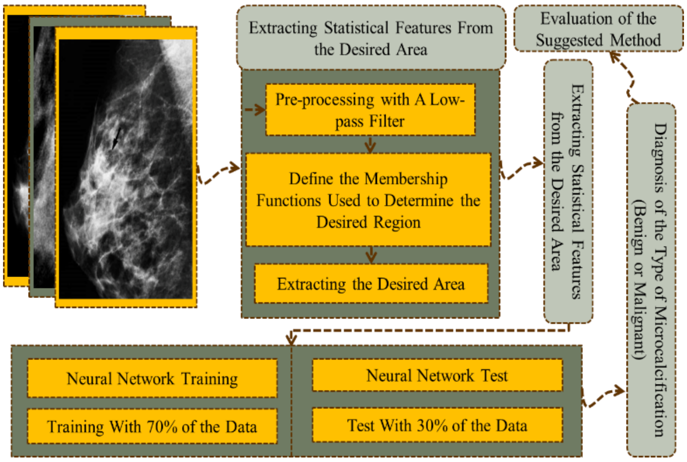

Figure 1. *Block diagram of the proposed method for the detection of fine particles*

Database

The MIAS (Mammographic Image Analysis Society) image database serves as the primary dataset for this research [38]. This database encompasses a total of 322 mammography images, each representing one of six distinct types of breast diseases in women. Within the dataset, there are 115 images obtained from affected individuals and 207 images from healthy individuals. Among the images from affected cases, there are 65 depicting benign conditions and 50 depicting malignant cases. These diseased images, comprising both benign and malignant instances, play a crucial role in training and evaluating the proposed breast cancer detection method, contributing to the research's overall effectiveness and accuracy.

Pre-processing

The quality and differentiation of existing mammography images often pose challenges due to factors such as limitations of mammography devices. These challenges manifest in the difficulty of distinguishing between different tissues in the images, including fat tissues, lactating tissues, and lymph nodes. Additionally, microcalcifications, being very small particles, are scattered within a specific part of the breast tissue, further complicating their detection. So, improving image quality through pre-processing techniques can help minimize noise, enhance contrast, and highlight relevant features, ultimately aiding in the detection of subtle abnormalities and improving the overall accuracy of breast cancer detection methods. In image processing, pixels can be divided into two categories: low frequency pixels and high frequency pixels. Low frequency pixels have a small difference in brightness compared to their neighboring pixels and are typically found in smoother regions of the image, representing gradual changes in intensity. On the other hand, high frequency pixels have a significant difference in brightness compared to neighboring pixels and are commonly found at edges and noisy regions, signifying abrupt changes in intensity and detailed features.

Since microcalcifications typically appear as lighter grains compared to the surrounding breast tissue in mammography images, enhancing the image to improve the visibility of high-frequency pixels is essential. An averaging filter, a type of low-pass filter, is employed to reduce noise by allowing low-frequency pixels to pass through while modifying high-frequency pixels. Low-frequency pixels are those with minimal brightness differences compared to their neighboring pixels, representing smoother or quieter regions in the image. In contrast, high-frequency pixels exhibit significant brightness variation with their neighboring pixels, such as edges and noise. By applying the low-pass filter, the image becomes smoother, with edges and noise being subdued to some extent. Afterward, to enhance the edges and improve the initial contrast, a local fast Laplacian filter is applied to the image. This process results in an image with higher contrast and sharper edges, providing better visual quality for the accurate identification of microcalcifications compared to the original image.

Extracting the desired area

In order to extract the desired area, using an algorithm based on the fuzzy method, the areas suspected to be caused by calcium fine grains are determined. Fuzzy clustering is considered as a soft segmentation method.

According to the fuzzy clustering method, FCM algorithm is a common method in image clustering because it has strong features for fuzzy points and can retain more information than hard clustering.

The conventional FCM algorithm performs well on noise-free images but is highly sensitive to noise and fake images. To effectively use the fuzzy method, it is essential to distinguish between healthy areas and areas containing fine microcalcification. The images in the MIAS database have dimensions of 1024x1024, and the average radius of the regions identified as fine grains is approximately 17. Consequently, a window size of 16x16 is considered appropriate for detecting fine-grained areas using thresholding. In regions with microcalcifications, the brightness is higher than in other areas. By employing a 16x16 window and comparing the average light intensity of each window with its neighboring windows, microcalcified areas can be extracted. These regions exhibit a high average light intensity, and their maximum light intensity should exceed a predefined threshold. By assessing each pixel's status and classifying them into three categories: suspicious, healthy, and microcalcification, based on their block's average light intensity, finer details can be captured during breast cancer detection in mammography images.

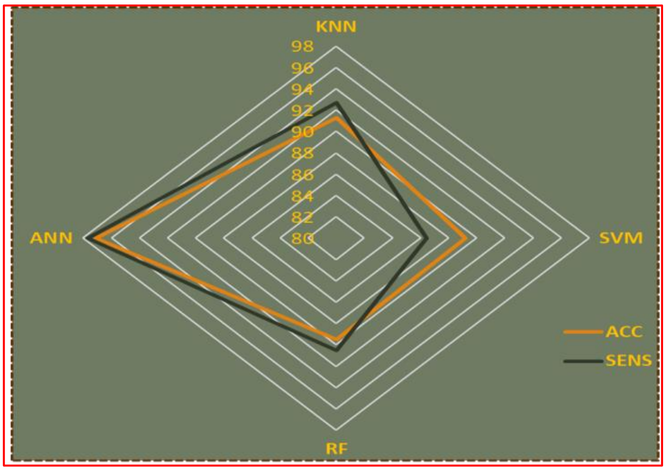

Figure 2. *Comparing the classification results of statistical features extracted from the desired area*

Post-processing processes

In the post-processing stage, the wear operator is utilized on the image to further refine the detection results. This operator helps eliminate areas that are not genuinely suspected to contain microcalcification or may have been wrongly diagnosed as microcalcification due to empirical values used during the initial processing. The wear process is applied based on the dimensions of the structural element, allowing for the targeted removal of false-positive or irrelevant regions. This step helps improve the accuracy and reliability of the detected micro-calcified areas.

Feature extraction

In this research, a set of statistical features has been utilized to extract important characteristics from the desired area. These features include curve elongation, entropy, mean, variance, standard deviation, quartiles, median, range, mode, skewness, minimum, and maximum.

Classification

In this research, features extracted from a feed-forward neural network using the back-propagation training algorithm are employed to classify micro-granules into benign and malignant categories. The network architecture includes a hidden layer, and the data is divided into 70% for training, 15% for validation, and 15% for testing. Different configurations of hidden layer neurons are explored to optimize the network's performance.

Results

In the proposed method, the desired area is initially extracted using the fuzzy method, and then the images are presented to a breast cancer specialist for further evaluation. The specialist's input helps to distinguish areas suspected to contain microcalcification. A comparative analysis is conducted between the areas identified by the specialist and those extracted using the proposed method, based on accuracy and sensitivity criteria. By assessing the agreement between the two sets of identified areas, the method's performance is evaluated and validated, ensuring its efficacy. If we define T^P as the number of regions correctly identified as microcalcification by both the proposed method and the breast cancer specialist, F^N as the number of regions that are actually microcalcification but were not diagnosed as such by the proposed method, F^P as the number of regions incorrectly identified as microcalcification by the proposed method but not identified by the specialist, and T^N as the number of regions correctly identified by both the proposed method and the specialist, the two evaluation criteria, accuracy (A_C) and sensitivity (S), can be defined as follows [39,40]:

$$A_C = \frac{T^N + T^P}{F^N + F^P + T^N + T^P} \tag{1}$$

$$S = \frac{T^P}{T^P + F^N} \tag{2}$$

in which T^P, T^N, F^P and F^N express true positive and true negative, false positive and false negative, respectively [41,42]. The proposed method demonstrates a high accuracy of 97.50% in identifying micro-calcified areas, indicating that it correctly identifies 97.50% of the regions compared to the specialist's assessment. Additionally, the method exhibits a sensitivity of 98.13%, highlighting its ability to accurately detect true positive regions compared to the total number of actual microcalcification present in the images. Table 1 provides a comparison of the proposed method with two reference studies [43] and [44], demonstrating its higher accuracy. The MIAS database is used in all studies, and the proposed method's step-by-step approach ensures accurate identification of micro-calcified areas, leading to improved classification accuracy.

Table 1. *Comparison of the precision of detecting the fine grain area of the proposed method with other methods*

Research	Model provided	Average accuracy
[43]	2 D-CNN	94.1%
[44]	RNN	95.9%
Suggested method	Neural network	97.1%

After extracting the desired regions, the research proceeds to classify them into two groups: benign and malignant. To ensure reliable and robust classification, the k-fold method is employed with ten repetitions for both training and testing. The dataset is divided into three subsets randomly, with 70% allocated for training, 15% for validation, and 15% for testing. This random partitioning ensures an unbiased and representative distribution of data across the training, validation, and testing sets. The classification performance of the neural network is evaluated with varying numbers of hidden layer neurons. Table (2) presents the confusion matrix for a network with one hidden layer containing 10 neurons. With this configuration, a classification accuracy of 87% is achieved for the test data. However, when the number of hidden layer neurons is increased to 20, the classification accuracy improves significantly to 95%. This outcome demonstrates the positive impact of increasing the network's complexity and capacity on its ability to discern between benign and malignant regions in mammography images, leading to more accurate and reliable detection results.

Table 2: *The accuracy obtained from the classification of benign and malignant micro-granules based on the number of neurons.*

Number of neurons	Hidden layer	Precision
10	1	87%
20	1	85%

To comprehensively evaluate the proposed method, several classifiers, including K-nearest neighbor (KNN), random forest (RF), and support vector machine (SVM), are employed in addition to the neural network. The k-fold method with ten repetitions is utilized for training and testing across all classifiers. Figure 2 displays the results obtained from different classifications, with K-nearest neighbor shown in blue, support vector machine in orange, random forest in gray, and the neural network in yellow.

It is evident from the results that the neural network, specifically with 20 neurons in the hidden layer, outperforms the other classifiers. The neural network exhibits the highest accuracy, achieving an average accuracy of 97.15%. In comparison to K-nearest neighbor, support vector machine, and random forest methods, the proposed approach consistently yields the most accurate and reliable breast cancer detection.

Conclusion

This research presents a fully automated technique for detecting and classifying microcalcifications in mammography images, with the dual objectives of improving diagnostic accuracy and assisting clinicians in breast cancer screening. Our approach not only delivers precise categorization results but also highlights the specific locations of microcalcifications, offering valuable visual annotations that enhance interpretability. The proposed method employs a fuzzy clustering algorithm to accurately extract microcalcified regions, achieving a precision rate of 96.7% and a sensitivity rate of 97.2%. The fuzzy clustering approach allows for the effective handling of noise and uncertainty within the mammography images, ensuring accurate segmentation of calcified regions, even in low-quality images. Following the extraction, relevant features are computed and used for classification, distinguishing between benign and malignant microcalcifications. To classify the microcalcifications, a feed-forward neural network with the error propagation training technique was applied. This neural network demonstrated superior performance compared to conventional classifiers, such as Support Vector Machine (SVM), k-Nearest Neighbors (KNN), and Random Forest (RF). The proposed technique achieved an overall classification accuracy of 97.5%, a sensitivity of 98.1%, a positive predictive value of 98.3%, and a negative predictive value of 96.3%, highlighting its robustness in detecting malignant microcalcifications while minimizing false negatives. These results reflect a significant improvement over traditional methods, where lower accuracy and sensitivity rates have been observed. By leveraging the combined strengths of fuzzy clustering for feature extraction and neural networks for classification, this method has shown great promise in enhancing diagnostic performance. The comparative analysis with SVM, KNN, and RF classifiers further underlines the superiority of the proposed approach in both precision and sensitivity. The findings of this study suggest that this automated technique could become a valuable tool for radiologists, improving decision-making in breast cancer screening, diagnosis, and treatment planning. Given the high identification accuracy and classification precision achieved, the proposed strategy has the potential to reduce diagnostic errors, support earlier detection of malignancies, and ultimately improve patient outcomes in breast cancer care.

In this study, we evaluated our proposed method using the MIAS database, a widely recognized dataset for mammography research. However, to further validate the robustness and generalizability of our approach, future research will focus on applying this method to additional mammography datasets. Testing on larger and more diverse datasets, such as DDSM (Digital Database for Screening Mammography) and INbreast, will allow us to comprehensively assess its performance across different populations, imaging conditions, and clinical environments. Expanding the analysis in this manner will help solidify the potential of our technique as a reliable diagnostic tool across broader contexts.

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