ORIGINAL ARTICLE

Early Detection of Cancer using Mammograms with Advanced Artificial Intelligence (AI) Algorithms for Breast Lesions

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Abstract

Background: Breast cancer is the second most common cancer and leading cause of cancer death among women worldwide.

Objective: To early detect breast cancer by application of computerized methods on mammography images.

Methods: This study is based on the computerized detection of lesions on mammograms which was conducted at the Radiation Therapy Unit, AIMC/Jinnah Hospital Lahore during 2021-22. A total of 322 cases from the Image Processing Archive (PEIPA) MIAS database were retrieved. The case can be described by seven attributes. The attributes include the MIAS database reference number, the type of background tissue (F-fatty, G-fatty-glandular, or D-Dense-glandular), and more.

Results: Accuracy is calculated to check the performance of the method. Our algorithm produced good results with an accuracy of 98.12 % in the detection of cancer regions in images. The accuracy achieved for benign cases is 96.1% and for normal cases is 98.2% respectively.

Conclusion: Based on this method, a tool for improved breast cancer detection can be created.

Keywords: *Tumor, Computer-aided detection, benign, malignant, mammogram.*

INTRODUCTION

Medical images reveal the properties of various human body tissues for disease diagnosis by observing how they reflect, transmit, or emit energy [1]. These properties are related to the actual structure, composition, and function of the body [1]. The art of medical imaging involves finding connections between tissue properties, image features, human anatomy, metabolism, physiology, chemistry, and biology, and how these aspects are associated with disease. This is the aim of interpretation [2]. Shortly after the discovery of X-rays by Roentgen in 1895, this radiation was used as a medical tool in many countries. Becquerel discovered the β-particles. Marie Curie discovered the naturally occurring radioactive elements radium, thorium, and polonium's α-particles. In 1900, Villard identified the third form of radiation called γ-rays. X-rays are still an important imaging tool for diagnosing many disorders despite the emergence of other technologies [3]. X-rays are produced when an X-ray tube beam passes through a body part. The amount of X-rays that are absorbed by the material depends on its composition and density. X-rays that pass through the object are recorded on sensitive films [4].

The term "cancer" refers to a group of diseases in which abnormal cells proliferate rapidly and uncontrollably beyond their normal boundaries, invade adjacent body organs, and eventually metastasize to other parts of the body through the lymphatic and blood systems where they form new tumors [5]. It has been reported that there were 19,292,789 new cancer cases and 9,958,133 deaths due to cancer in 2020. There are 32.6 million people who are living with cancer within five years of diagnosis. Breast cancer is the second most common cancer and the fifth leading cause of cancer mortality worldwide. It is also the second leading cause of cancer death among women [6, 7]. Early detection of breast cancer is essential for patient care and survival [8]. Although mammography is the best method for early detection of breast cancer, it has some limitations [9]. The expertise of the radiologist and the quality of the medical image are key factors in medical image interpretation. Studies have shown that radiologists miss some of the abnormalities in images. The main causes of these errors are observer limitations and the complexity of the medical images [10]. CAD can be defined as "the use of computer algorithms to assist the image interpretation process". It is also known as computer-aided detection because most applications are about detection. The computer and image processing techniques provide valuable assistance in identifying the malignant area [11]. Over the past 20 years, the development of computer-aided detection has increased. The concept of computer-aided detection is to provide second opinions to support radiologists in analyzing medical images. Different studies on CAD have shown that it reduced the workload and missed cancers and improved the accuracy and consistency of radiologists [12, 13] (**Fig. 1**).

Related Work

Mammography is the most reliable and efficient method for detecting breast cancer in its early stages [14]. The use

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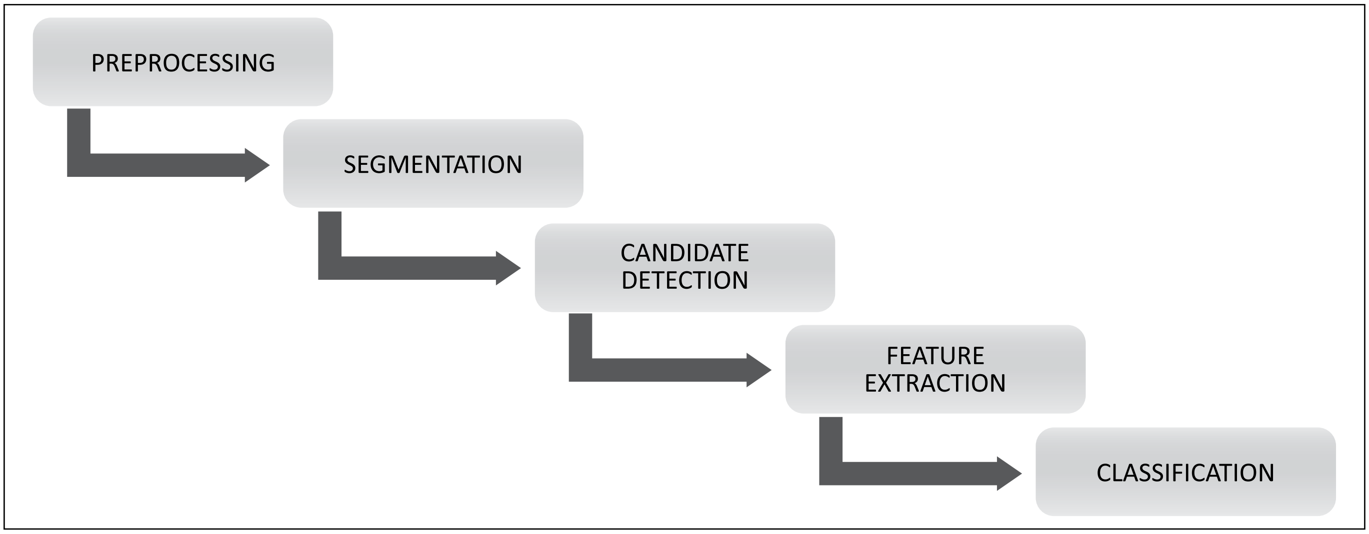

Fig. (1): The process of this research work.

of computer assistance is important to help radiologists in mammography because of the complex breast structure, low probability of breast cancer, and subtle differences among findings [15]. The performance of CAD with FFDM in detecting breast cancers was evaluated on mammographic cases that were confirmed by biopsy with FFDM [16]. Skaane *et al.* compared the performance of full-field digital mammography (FFDM) and digital breast tomosynthesis (DBT) with that of reconstructed two-dimensional images and concluded that the routine clinical use of DBT and reconstructed two-dimensional images is acceptable [17]. Durand *et al.* screened 17955 mammograms and found that the cancer detection rate was 5.9 cancers per 1000 examinations in the (2D+3D) screening examinations and 5.7 cancers per 1000 examinations in the 2D screening tests [18]. Dheeba *et al.* proposed a new method for detecting breast cancer in digital mammograms using Particle Swarm Optimized Wavelet Neural Network (PSOWNN) and showed that it outperformed conventional classifiers in terms of accuracy, with a sensitivity of 94.167% and a specificity of 92.105% [19]. McDonald *et al.* reported that digital breast tomosynthesis (DBT) combined with digital mammography (DM) reduced the number of false-positive tests [20]. Gu *et al.* stated that automated 3D ultrasound image segmentation is essential for the clinical diagnosis of breast cancer [21]. Guo *et al.* proposed a new breast ultrasound image segmentation algorithm based on a neutrosophic similarity score (NSS) and demonstrated that it can accurately and effectively segment breast ultrasound images [22]. Jung *et al.* found that the computer-aided detection (CAD) system on mammography was helpful for breast radiologists and radiology residents to improve their diagnostic performance [23]. Van Zelst *et al.* studied the effect of dedicated Computer Aided Detection (CAD) software for automated breast ultrasound (ABUS) and found that it increased the radiologists' screening performance for cancer detection [24].

SUBJECTS AND METHODS

Mammography Procedure

Mammography is a vital medical imaging technique used for early diagnosis and detection of breast diseases. X-rays are the most common form of radiation used for imaging a body part [25]. The image produced by mammography is called a mammogram. Mammography is an X-ray examination of the breast like other diagnostic images [26]. The X-ray beam is attenuated by different tissues as it passes through the breast. The differences in absorbed dose are recorded on the X-ray

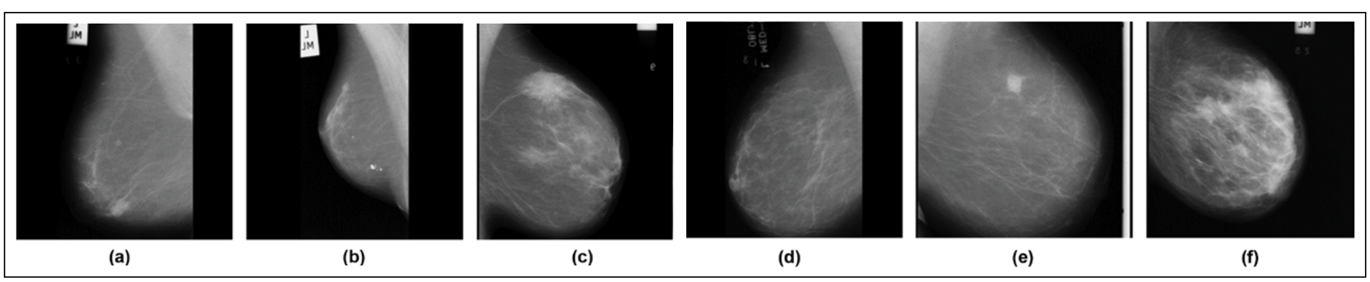

Fig. (2): Image of six abnormal types: **(a)** circumscribed mass, **(b)** asymmetry, **(c)** architectural distortion, **(d)** calcification, **(e)** ill-defined masses, and **(f)** spiculated masses.

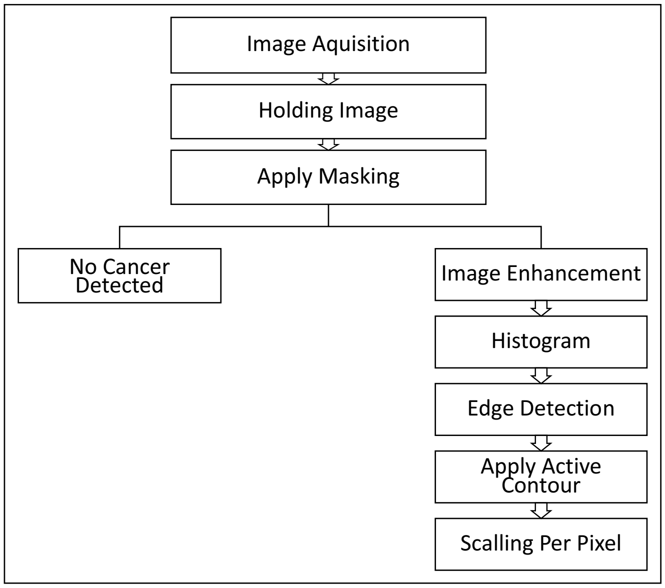

Fig. (3): Segmentation Process.

image, which reflects the specific characteristics of the breast tissue. For a clear examination, each breast is compressed during the procedure. Radiation from an X-ray tube is emitted during the process, passing through the breast and being captured on film or an electronic device. The mammography views are described as craniocaudal from a top view and as mediolateral from a side view. The mammogram of six abnormal breasts is shown in **Fig. (2)**.

Data Set

Breast cancer is a major concern for many women worldwide. Several mammography databases have been created to research the early diagnosis of breast cancer. We used 322 cases from the Pilot European Image Processing Archive (PEIPA) MIAS dataset to analyze female breast cancer. The case can be described by seven attributes. The attributes include the MIAS database reference number, the type of background tissue (F-fatty, G-fatty-glandular, or D-Dense-glandular), and more. The types of abnormality present in this case are calcification, well-defined/circumscribed masses, speculated masses, ill-defined masses, architectural distortion, asymmetry, and normal. The labels for the types that indicate the severity of abnormality are benign and malignant. The class labels are assigned the letters B for benign and M for malignant. The fifth and sixth attributes give the x, y image coordinates of the center of the abnormality. The last attribute gives an approximation of the radius (in pixels) of a circle enclosing the abnormality. The data are organized in pairs of left and right mammograms of a single patient. The mammography images are 1024 pixels by 1024 pixels in size and are centered in the matrix. The clusters are influenced by the center positions and radii of the calcifications.

Detection of Cancer

This section describes the methods used to detect breast cancer using mammography images. The segmentation section involves thresholding and edge-based technique. The research steps are shown in **Fig. (3)**.

This study aimed to provide a computerized method for segmenting mammographic images to improve the performance of mass characterization. Mammographic images were acquired and a masking filter was applied to determine the presence or absence of malignancy according to our criteria. The image was enhanced and sharpened to remove any noise from the mammograms in case of cancer presence. A histogram was generated after applying thresholding. The Sobel edge detection technique was used to mark the boundaries of the object. The active contour method eliminated the surrounding tissue and extracted the malignant region. The accuracy of the result was verified by scaling pixels to pixels using ground truth.

a) Thresh-Holding

The Thresh-Holding technique is frequently used to separate the foreground and background of photographs. This method arrived at an intensity value by taking into account the image's intensity levels. The coordinate function is modified following the pixel intensity of the image.

Consider I (i, j) to be an image,

$$I(I,j) = \{o,\ f(I,j)<G\}$$
$$\{1,\ F(I,j)>= G\}$$

Global thresholding uses global data, such as the histogram, to segment the image. Usually, breast masses are brighter than other tissues and are used to set global threshold values. The abnormal regions produce extra peaks, unlike the normal region, which has only one peak. The threshold value that was used to segment breast cancer was based on the intensity levels of its neighboring pixels; local thresholding determined a local threshold value for each pixel.

An initial value for G was chosen to obtain the threshold value. The image was divided into two different pixel classes based on the value of G. One class contains pixels with values higher than G, while the other class contains pixels with values lower than G. The intensities of the two classes were computed and the results were used to update the value of G.

b) Edge-Based Segmentation

Edge detection methods are based on the changes in the grey level of the image. The rate of change in the grey level is estimated using derivatives for edge detection. The most commonly used edge detection operators are

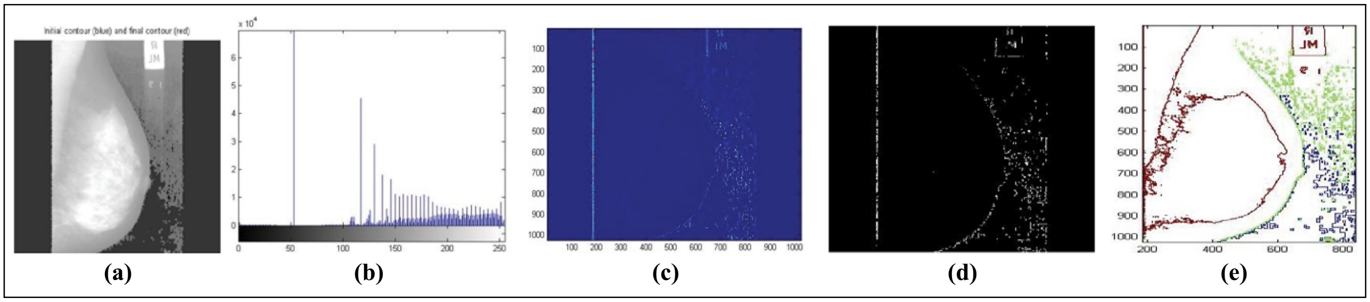

Fig. (4): Application of the computerized method for detection of a normal mammogram. (a) Enhancement of normal, (b) Histogram for normal image, (c) Thresh-holding, (d) Sobel edge detection, (e) Active contouring.

the Prewitt operator, Sobel operator, Roberts operator, and Laplacian of Gaussian (LoG) operator.

The Sobel operator computed a 2-D spatial gradient measure and considered the regions with a high spatial frequency that corresponds to edges on a mammography image. The Sobel operator determined the absolute gradient magnitude at each point on a mammography grayscale image. The Sobel operator has a value of zero at a point with constant intensity and is a vector at an edge point with the direction from a darker to a brighter region.

An active contour is an energy-minimizing spline that is pulled towards boundaries, edges, and lines under the influence of external forces and image forces. An active shape can be described as a curve. The curve traverses the spatial domain of the image to minimize the energy function.

The study was approved by the Ethical Review Board, Allama Iqba l Medical College, Lahore, Pakistan, vide reference No. 194/23/12/2021/52 ERB Dated 17.02.2022.

RESULTS

We have collected the MIAS data for various categories of mammograms. With the use of an enhancement approach, we have sharpened and brightened the photos to make it easier to see tiny cancer. We then extracted characteristics from the improved image. We took a histogram of the improved image, which has 266 different hues. The histogram gave us a range of gray levels, from 0 to 255. If an irregularity was found in the processed image, we were able to determine which area is more congested and applied threshold-holding to that image.

For calculating the accuracy we have used TN (True Negative), FN (False Negative), TP (True Positive), and TN (True Negative).

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$Accuracy = (TP + TN)/(TP + FP + TN + FN)$$

Fig. (4) depicts the computer algorithm that was used on the typical mammography image and its results. The process of picture enhancement is depicted in **Fig. (4a)**, followed by the creation of a histogram in **Fig. (4b)** and the application of thresholding in **Fig. (4c).** Sobel Mammogram edges are described by edge detection in **Fig. (4d)**, and active contour generates output that is compared to ground truth **Fig. (4e)**.

Fig. (5) shows the suggested computerized method used on cancer-positive mammograms, along with the use of masking, histogram computation, and picture enhancement. The edges of cancer discovered in mammography are accurately described by the edge detection system. Active contouring is displayed in the figure above.

Precision, recall, true positive, false positive, and other metrics were used to evaluate the cancer cases' detection

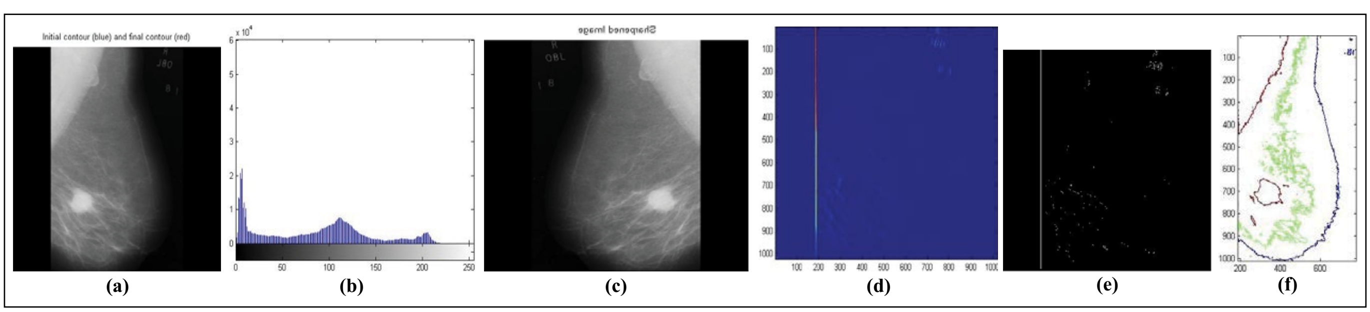

Fig. (5): Application of the computerized method for the detection of cancer on a mammogram. (a) Cancer image, (b) Histogram, (c) Enhancement, (d) Thresh-holding, (e) Sobel edge detection, (f) Active contouring.

Table 1: Cancerous images result.

Sr. No.	Image Name	TP	TN	FP	FN	Precision	Recall	Accuracy (%)
1	MDB003	0.0116	0.9253	4.2820e-04	0.0627 0.0116	0.9644	0.1560	93.6871
2	MDB111	0.0173	0.9336	0.0069	0.0422 0.0173	0.7151	0.2911	95.0890
3	MDB117	9.4986e-04	0.9896	00014	0.0080 9.4986e-04	0.3968	0.1063	99.0566
4	MDB120	0.0035	0.9407	0.0075	0.0483 0.0035	0.3145	0.0667	94.4187
5	MDB132	1.2207e-04	0.8329	0.1609	0.0060 1.2207e-04	7.5799e-04	0.0198	83.3034

Table 2: Benign images result.

Sr. No.	Image Name	TP	TN	FP	FN	Precision	Recall	Accuracy (%)
1	MDB005	0	0.9922	0	0.0078	NaN	0	99.2167
2	MDB015	3.4428e-04	0.9784	3.1719e-05	0.0212 3.4428e-04	0.9025	0.0160	97.877 6
3	MDB021	9.9945e-04	0.8964	0.0145	0.0881 9.9945e-04	0.0644	0.0112	89.7384
4	MDB025	6.1989e-05	0.9740	0.0104	0.0156 6.1989e-05	0.0059	0.0040	97.4016
5	MDB063	0.0091	0.9444	0.0127	0.0338 0.0091	0.4177	0.2125	95.3490

Table 3: Normal images result.

Sr. No.	Image Name	TP	TN	FP	FN	Precision	Recall	Accuracy (%)
1	MDB006	0	0.9978	0.0022	0 0	0	Not a Number (NaN)	99.7809
2	MDB009	0	0.9898	0.0102	1.0490e-05 0	0	0	98.9837
3	MDB011	0	0.9999	6.9618e-05	0 0	0	NaN	99.9930
4	MDB014	0	0.9764	0.0236	0 0	0	NaN	97.6398
5	MDB022	0	0.9872	0.0128	0 0	0	NaN	98.7180

Table 4: Performance of proposed Technique.

Mammogram images	PRECISION (%)	RECALL (%)	ACCURACY (%)
CANCEROUS	96.4	55.4	98.12
BENIGN	90.2	52	96.1
NORMAL	96.8	68	98.2

accuracy and false negatives (**Table 1**). Through our strategy, the benign and typical pictures are categorized. **Table 1** shows a small number of results for cancer cases, **Table 2** shows accurately segmented data for benign cases, and **Table 3** displays findings for normal instances. Overall performance of the proposed research as we observed the results given in **Table 4**.

DISCUSSION

We used Sobel edge detection techniques as an edge detection tool because they are among the best at detecting both large and small patches of malignancy. The advantage of Sobel is that it improves edge detection. Then, we used Active Contouring to locate the exact position of the cancer.

An active contour segments a 2-D grayscale object into the foreground (object) and background regions. The resulting image has a black background (logically false) and a white foreground (logically true). The mask specifies the initial state of the active contour; the mask is a binary image. The boundaries of the object region(s) in the mask, which are white, determine the starting point of the contour when segmenting an image. For classification, we also applied the features that were extracted using case-based reasoning. Then, to evaluate the accuracy of our method, we obtained the ground truth of the original image. The result is 98.12% accuracy. Danilo Cesar Pereira and colleagues investigated the segmentation and detection of breast cancer using a combination of wavelet analysis and genetic algorithm [27]. The method reported a 79% AOM. Kumar *et al.* proposed an image-processing technique for detecting breast cancer on mammograms [28].

Kuan *et al.* studied deep learning methods for the detection of lung cancer with specificity of 73% [29]. Early detection of cancer regions in mammograms can reduce the mortality rate in breast cancer patients. Research is needed to improve the methods currently used for effectively detecting cancer in mammography images. A technique should be developed to accurately segment cancerous regions to overcome this limitation. This goal motivates us to develop a more accurate detection technique. We combined various image processing techniques to create this method to accurately detect and segment breast cancer in mammograms. Real-time detection also considers time consumption. It is also taken into account in this study. This method first detects malignancy in mammograms before segmenting it. Our method has produced improved results with an accuracy of 98.12% and a precision of 96% for cancer in mammograms.

CONCLUSION

This research focuses on the early detection of breast cancer through a computerized method applied to mammography images. The objective is to reduce the workload, improve accuracy, and minimize missed cancer cases, thus enhancing the performance of radiologists. The study was conducted using 322 cases from the PEIPA MIAS database at Radiation Therapy, AIMC/Jinnah Hospital Lahore. The proposed methodology involves the use of a computer algorithm for lesion detection, including the application of a mask to define initial conditions, Sobel edge detection for boundary identification, and the active contour approach for isolating cancer regions. The results indicate a high accuracy of 98.12% and precision of 96.4% in detecting cancer regions within the mammography images. The findings suggest that this method could serve as a basis for developing an improved tool for breast cancer detection. With breast cancer being a leading cause of cancer mortality among women worldwide, early detection through computer-aided diagnosis has the potential to significantly impact patient care and survival rates

ETHICAL APPROVAL

The study was approved by the Ethical Review Board, Allama Iqbal Medical College, Lahore, Pakistan, vide reference No. 194/23/12/2021/52 ERB Dated 17.02.2022. All procedures performed in studies involving human participants were following the ethical standards of the institutional and/ or national research committee and with the Helsinki Declaration.

CONSENT FOR PUBLICATION

Written informed consent was taken from the participants.

AVAILABILITY OF DATA

The data set may be acquired from the corresponding author upon a reasonable request.

FUNDING

Declared none.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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AUTHOR'S CONTRIBUTION

All the authors contributed equally to the publication of this article.

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