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An Automatic Breast Cancer Diagnostic System Based on Mammographic Images Using Convolutional Neural Network Classifier

Maria Jubeen[1], Hameedur Rahman[2,*], Ata Ur Rahman[3], Samiya Abdul Wahid[2], Azhar Imran[3], Amanullah Yasin[3] and Imran Ihsan[3]

[1]Department of Computer Science, Institute of Southern Punjab, Multan, 66000, Pakistan
[2]Department of Computer Games Development, Faculty of Computing & AI, Air University, Islamabad, 44000, Pakistan
[3]Department of Creative Technologies, Faculty of Computing & AI, Air University, Islamabad, 44000, Pakistan
[*]Corresponding Author: Hameedur Rahman. Email: hameed.rahman@mail.au.edu.pk

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Abstract: World's second most occurring cancer is breast cancer. Prediction of disease is one of the most challenging tasks and there are many factors that effect this type of diagnosis like the ability of visual perception. This paper proposed a Convolutional Neural Network (CNN) based proper method for analyzing the earliest signs of breast cancer with the help of mammogram images. The main goal of proposed system is to identify the disease of breast cancer at early stages. Due to this reason, Mammographic image analysis society (MIAS) dataset is used. There are three hundred & twenty two (322) mammograms in the dataset, with 209 images of normal breasts and 133 images of abnormal breasts. While abnormal breasts are further classified as benign (62 images) and malignant (51 images). To implement this system, python library Keras and Tensor Flow libraries are used along with deep learning model CNN. Convolutional Neural Network (CNN) has been shown to be effective in detecting breast cancer in mammography images with 70% accuracy rate, according to promising testing data. The proposed system will enable the radiologist in detecting breast cancer in early stages.

Keywords: Cancer; Mammography; Neural Networks; Benign; Malignant.

1. Introduction

After lung cancer, breast cancer is the second most frequent cancer worldwide. The most common malignancy in women is breast cancer all over the world. The ratio of deaths due to Breast Cancer is almost 23% while 14% deaths occurred due to other types of cancer amongst women [1]. According to statistical calculation of WHO, every year, more than 1.5 million women around the world are affected. According to the American Cancer Society's annual report for 2017, in women there were roughly 252,710 new cases of malignant tumors diagnosed while 2470 new cases in males (Breast Cancer statistic, 2019). Breast cancer can be detected early and treated more successfully, lowering mortality and improving outcomes. Among Asian countries in Pakistan the position is very alarming. Every year 90,000 cases are reporting, out of which 40,000 cases end with death. Too early detection of breast cancer can lower the death rate. BC is usually painless in its early stages and is easily treated, which is why screening is critical for early discovery. All medical organizations recommend screening for women after 30 years. 42 million screenings are performed each year in the USA and UK. Breast cancer has been detected using a variety of techniques, including artificial neural networks (ANN), support vector machines (SVM) etc. During the screening process, radiologists review the mammography images. Because some cancer cases were wrongly diagnosed as normal instances, a skilled radiologist is essential to give an error-free diagnosis. Mammography is a highly effective, extensively used tool for detecting breast cancer at early [2] stages because of low expense and high sensitivity to minor lesion. It can detect even the tiniest changes in the body. Prediction of disease is one of the most challenging tasks. Data mining has become a trending technology in research and for medical domain applications. The main goal of this research is to differentiate between benign and malignant cancerous images which help in diagnosis and treatment of cancer patients. For feature extraction in breast cancer, other techniques such as fuzzy logic and neuro-fuzzy systems are applied to distinguish between abnormal and normal categories [3]. The goal of this research is to develop Breast Cancer Diagnostic System (BCDS) detection based on AI using mammographic images and focus on convolutional neural network (CNN) [4]. These algorithms help in differentiating between cancer images. Successful diagnosis helps in treatment of cancer which can save the precious life of women. The main aim of the system is to detect malignant or benign in mammogram images which are provided to system. BCDS is a diagnostic tool for radiologists that helps them minimize the number of incorrect diagnoses and improve accuracy of their diagnoses. Pre-processing, segmentation, and feature extraction are among the processing techniques used by BCDS. In order to make an accurate diagnosis, all these steps must be accomplished. The main purpose of the project is the creation of a fully automated model for classifying mammography images, which will assist in disease diagnosis. Medical specialists review mammograms and recommend biopsy if anomalies are discovered in the proposed BCDS. Biopsy is a common clinical method for detecting BC, but it is a costly, time-consuming, and unpleasant treatment. At this point, the opinion of the radiologist is crucial. In the event of a misdiagnosis, the patient is subjected to an unneeded biopsy. This analysis can be automated to help radiologists improve their diagnostic accuracy, and such a system can be utilized as a second reader. BCDS is an AI-based system that uses mammography images to classify mammograms into one of two categories: benign (harmless to the body and does not spread to other parts of the body) or malignant (damages the body by progressing to other body parts and causes death).

The main contribution of this paper is:

- Diagnose breast cancer;
- Identify the clinical presentation of breast cancer.;
- The prediction should be 70% correct.
- System should tell the cancer is malignant or benign
- System should give an output image.

Many research projects in the field of breast tumor analysis have been completed in recent years. This proposed study is related to BCDS and mainly focuses on the diagnosis and detection of BC. Different techniques have been developed which have outstanding performance and can be utilized in real-time applications. In this portion, the existing work has been briefly summarized. Usually, mammograms consist of various noises and artifacts which makes mammography images difficult to understand and as a result the detection of breast cancer at early stages becomes vigorous and tough job [5].

Qiu et al. [6] by training CNN with a vast amount of time series data, they were able to predict the risk of breast cancer. While Sun et al. [7] deep neural networks were also applied to forecast the risk of breast cancer in the near future based on 420 mammography time series data. A deep feature-based framework for breast cancer diagnosis has been suggested, which uses CNN and a decision tree algorithm by Jiao et al [8]. CNN used [9] to abstract breast tumor models, and subsequently classified the tumor as benign or malignant. Ragab [10] to extract features from mammography classification, utilize the stretchily stretching function for preprocessing and the wavelet-based counter let approach. Raza [11] used NN for detection of breast cancer and created a foundation of automated cancer detection so that diagnoses can be done in the early stages. From mammograms, a breast cancer (BC) detection system based on mass detection, retrieval, and classification performed by an automated system proposed by Rahman [12]. Which predicts images as benign or malignant. For achieving the required result GBVS, NSCT, HOG, SVM, ELM are used which illustrate and demonstrate the practicality of a real-time clinical application using the proposed system. Arshad [13] proposed a breast cancer (BC) detection system for radiologists by using neural network (NN) implemented in MATLAB which extract features from mammography to classify breast cancer. In addition, this system provides patients with the option of making an online appointment book (OAB) with the appropriate radiologist and categorizes the cancer into three types Benign, Malignant and Normal. The rest of the document is formatted in such a way that the introduction was considered, and the suggested work is presented in this section. In the methodology section, the BCDS architecture and methodology for classifying mammograms for breast cancer analysis are discussed. Then we will present the results and discussion and the last section will describe the conclusion of the proposed work. Categorize cancer into three types Benign, Malignant and Normal.

2. Materials and Methods

2.1. Methodology

Breast cancer is one of the most dangerous types of cancer among all the cancers. Medical images such as mammograms and CT scans are of various importance for detecting breast tumor or brain tumor. For brain tumor [14] used segmentation and classification methods for detecting Brain tumor. There is a need for robust techniques which can be extract feature and apply machine learning techniques to diagnose the patients in early stages. While using machine learning algorithm the feature collection is a hand crafted which can lead to more inaccurate and impropriate results hence, we are using deep learning [15] for the automation of feature extraction. Salleh *et al* [16] uses a PCA and SURF for SVM to diagnose the subject through machine learning technique Rahman *et al* [17,18] applied a 3d visualization of BT while using augmented reality. The proposed system architecture is given in Figure 2 which shows all the inner module of the proposed system while Figure 1 is just the methodology for detecting BC using deep learning algorithm. All the prepressing steps are given below in details in pictorial form with the training, testing splitting (70% and 30%). Going through all the steps the system will generate the results or classification map and will make a prediction that the corresponding mammogram image is benign, malignant or normal.

Chemoprevention trials differ from normal therapeutic clinical trials in that asymptomatic, healthy patients are treated for a long time with a potential harmful intrusion. Race, geographic region, and other characteristics can influence how breast cancer is assessed. The current study offered a system to reduce breast cancer risk factors by ensuring accurate and error-free diagnosis. By using CNN which have dense model achieved remarkable results in segmentations. The suggested model possesses the behavior of all convolutional neural networks and multiscale dilated convolution for mammography imaging. As a result, BCDS model with CNN was designed as shown in Figure 2.

2.2. Dataset

Images from the mini-Mammographic Image Analysis Society (MIAS) collection were used to train and test the suggested CNN models. These are research datasets that are open to the public. The mammography images of 161 patients are included in the collection. Each patient's left and right mammography images are included in the collection. As a result, as indicated in Table 1, up to 322 images with high quality of 1024 x 1024 (width by height) number of pixels were included. A wide range of mammography images are included in the dataset. The dataset was divided into Normal, benign, and malignant classes. The original mini-MIAS dataset has a lot of inconsistencies. There are sixty-two (62), fifty-one (51) and two hundred & nine (209) cases of benign, malignant and normal respectively in this dataset. The dataset also includes some useful information about malignant tissues. Every image has a class of abnormality, background tissue, and a blob of center coordinates. Figure 3 depicts a sample format.

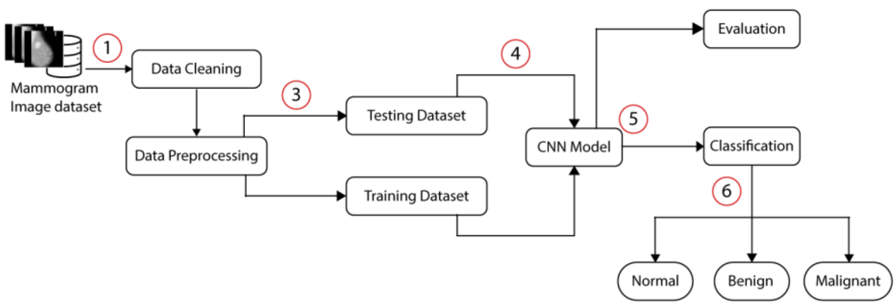

Figure 1. Methodology of BCDS

2.3. Pre-Processing

The quality of data in a mammography image is affected by artefact and the pectoral muscle, which has an impact on the classification system's performance [6]. To compute better and faster results of the classifier the pre-processing technique is important because it enhances the quality of raw mammography images, allowing for high accuracy. Around 30 areas in the mammogram image consist of breast region Background and pectoral cover the rest of the region. Separating the area of interest from the mammography image to learn the features from the image is required for training the CNN model. Before we feed the model the mammogram images will be preprocessed using the techniques adapted in [19]. Binarization is used to eliminate noise, while masking is used to extract the Regions of Interest (ROIs). Morphological procedures are used to describe and extract ROI from images. In BCDS the input is in the form of an image. From the input mammogram images the noise, labels, markers, and pectoral muscle are removed by using different pre-processing techniques including segmentations, Registration, image Harmonization, feature extraction. And other image operations are performed to adjust the colors of a given image to enhance their visual harmony.

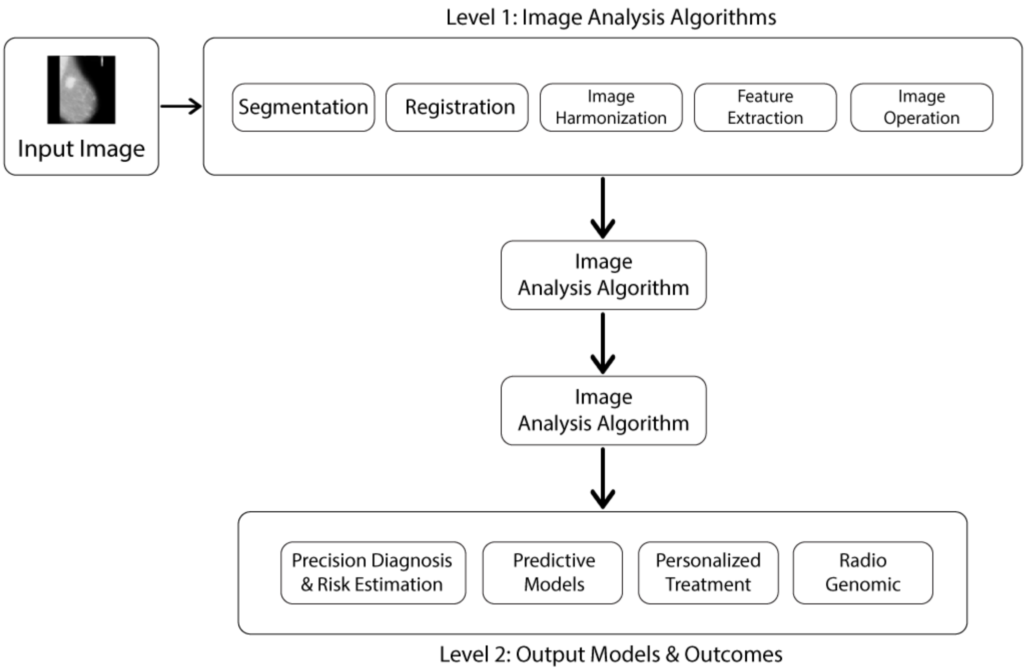

Figure 2. Architecture of BCDS

Table 1. Statistics of MIAS dataset

Classes	Benign	Malignant	Normal
No. of images	62	51	209
Total images		322	

2.4. Image Segmentation

Segmentation process separates the tumor areas from the background tissues in mammograms. To feed the CNN model 1024X1024 image size is too large and requires high computation power. To use 1024x1024 images in this case would be not good since in most images, only 20 of the images are made up of the region of interest (cancer tissue region). As a result, resizing allows us to constrict the image to the area of interest while maintaining high accuracy and reducing computation time (Tan & Sim, 2017). Images in large sizes the model spent a lot of computation time and power to learn unnecessary information which total wasting of time and which can affect the results and accuracy of the classifier. To achieve better results, the image will be resized 48 x 48 pixels, containing only the area of interest, for this the x and y coordinates are used which are provided by MIAS database. To enclose the tissues in circle the radius is used which is part of the database. For x and y coordinates and to obtain enclosed circle, the image is resized 48 x 48 pixels.

2.5. Feature Extraction

The accurate classification and diagnostic rate are mainly dependent upon robust features, particularly while dealing with mammograms. To extract the characteristics the features can be combined in a linear or nonlinear way, and they can be extracted with or without supervision [7]. Spectral, textural, and contextual variables are commonly retrieved from mammography images and explain changes in color quality, spatial distribution of color, tone, and denote information from the surrounding area from the interest region [8]. The feature extraction technique is used to overcome some of the drawbacks of breast thermography, such as (i) failure to diagnose small tumor, (ii) identifying the cause of high temperature other than tumor, and (iii) differences in interpretation by different physicians [20]. As a result, this technique supports extracting the best features from large datasets by selecting and combining variables into features, hence minimizing the amount of data. As a result, it is simple to process and can accurately and effectively describe the actual dataset.

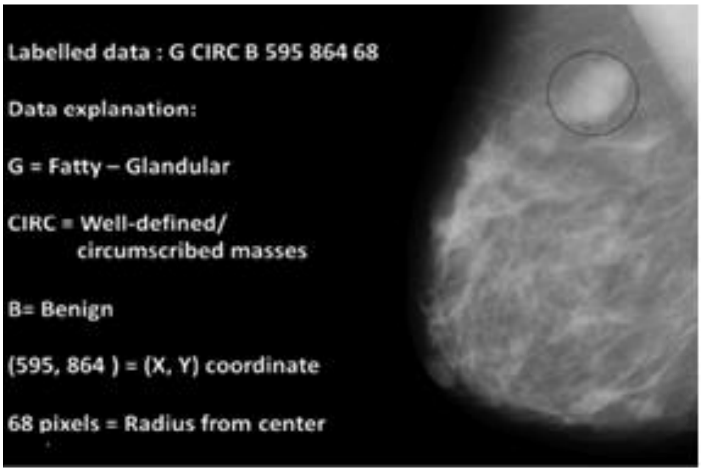

Figure 3. Tissues of MIAS dataset

2.6. Image Registration

Challenge of image registration arises when images are capture from many sen-sores, time, or subjects, and they must be integrated to analyze or visualize. Simply put, image registration is the process of overlaying two images, A (reference-image) and B (target-image), in a manner that they become spatially aligned. The task of matching the two images is analogous to calculating the transformation T, like that T (A) = B. This is also the same as the method of determining an unwrapped image B (derived from A) that is numerically near to B. Image registration is used to discover the best transformation or mapping function that will align one image to another. Different imaging modalities' complementing information can be integrated to help the radiologist diagnose breast cancer.

2.7. Image Harmonization

Photo editing is employed in composite photographs to achieve visual consistency by altering the appearance of the foreground to make it suitable with backdrop harmonization. Previous techniques to harmonizing composites relied on building encoder-decoder networks from the ground up, which makes learning a high-level representation of objects difficult for a neural network. To adjust the appearance of the image, we employ image harmonization.

2.8. Convolutional Neural Network

Convolutional neural network is a nonlinear deep neural network used in a supervised manner to learn latent and intrinsic characteristics and features from 2D and 3D images. These characteristics are useful for classifying and diagnosing anatomical and abnormal structures. In CNN, the input layer is followed by many convolutional, pooling and an output layer. Figure 4 is a graphical representation of CNN model.

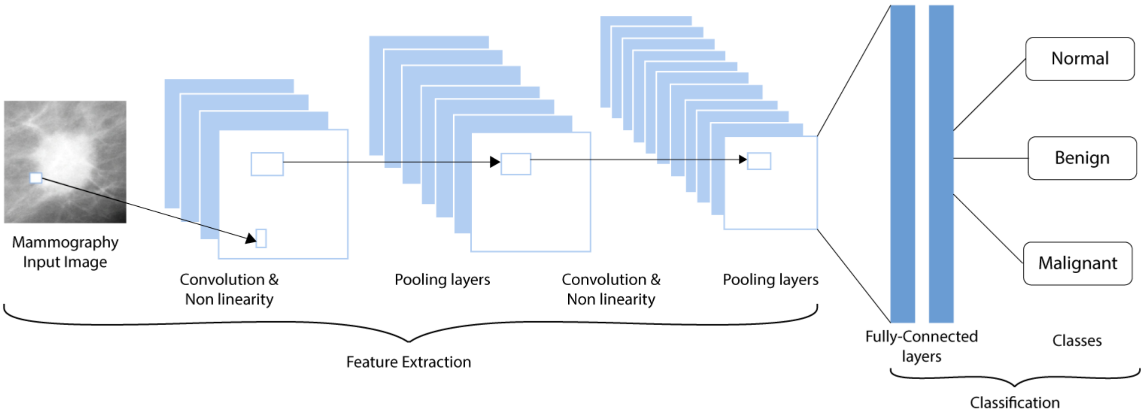

Figure 4. Architecture of CNN

The weight and bias are shared by numerous neurons in the convolution layer, which are spatially coupled. Convolution operation is used to convert the input image into a feature map in a standard convolution layer. The input image is mapped with a set of filters (kernels) at the convolution layer, which generates a new input feature map C_k Convolution is the name for this procedure. The value of a feature at a specific location (x, y) in k^{th} feature map of i^{th} layer as $C^i_k\,[x; y]$ which is calculated by equation 1.

$$C_k{}^i[x,y] \;=\; w_k{}^i\, I^i\,[x,y] \;+\; b_k{}^i \tag{1}$$

The dimension of the generated feature maps is reduced by using a pooling layer. In CNN models, generally there are three types of pooling operations are used like min pooling, max pooling, and average pooling. After a sequence of convolution and pooling processes, the output of the convolution layer is fed into the classification layer. Suppose R_l is the output of the last convolution layer hence it is calculated by equation 2.

$$R^l \;=\; f\,(I^l\,) \;=\; f_{relu}(\textstyle\sum_k \quad w_k f\,(I^{l-1})) \tag{2}$$

The number of filters used in the last convolutional layer is represented by k, w_k represents the kernel's weight and $f\,(I^{l-i})$ reflects the value of the activation of $(l-1)$ convolutional layer. To predict the probability of the class the softmax activation function is used for an input image in the classification layer, which calculates the class probability value using the following equation 3.

$$f_{so\,f\,tmax}(R^l\,) \;=\; \frac{exp(R^l)}{\sum exp(R^l\,)} \tag{3}$$

A spatially localized local connection pattern between neurons in adjacent layers. Such CNN features are extremely useful in solving vision or image-based challenges. According to research, CNN is highly good at detecting tumors. Emerging trends in the detection of brain tumors [5] and regarding the use of CNN for lung cancer detection.

3. Results

The proposed breast cancer screening method based on CNN yielded satisfactory results. The entire dataset was separated into two groups: normal and abnormal. The abnormal category was then divided into two categories: benign and malignant. Two methods were used for training and testing. The dataset is separated into two pieces with a 7:3 ratio in the first technique. One portion is used to train the CNN, while the other is used to test it. In the dataset, cancerous and non-cancerous cells are referred to as malignant and benign, respectively. The second way involves further subdividing of the abnormal class, which indicates six (6) types of different deviation present in breasts, including asymmetry, calcification, speculated masses, confined masses, architectural distortion, and miscellaneous abnormalities. Miscellaneous images were ones in which it was unclear if the images were benign or malignant. [21] To improve the performance and speed of learning of neural networks, pre-processing was used. Using varied filter sizes in CNNs to improve the accuracy of raw images. As a result, the accuracy is decided once the model parameters have been learned and fixed, with no additional learning. The findings were determined after CNN was implemented in both PyCharm and TensorFlow environments. On the MIAS dataset, an overall accuracy of 70% was achieved. I compare the present proposed system to the old system, which clearly demonstrates that the proposed decision support system has more capability and receives positive user feedback. Table 2 indicates the suggested system's response rate.

In comparison to existing systems. The proposed approach clearly performs much better than the present systems based on user satisfaction ratings.

Table 2. User Satisfaction rates of proposed system vs. existing systems

S.No.	Questions	Proposed System	BC detection Using NN	DSS for BC on invariant feature extraction	BC detection Using NN for radiologist
1	Which system do you like the most?	7	6	3	1
2	Are you comfortable with the system?	8	5	4	2
3	Is the system working properly?	7	5	4	4
4	Is the system working properly?	8	6	5	4
5	Does the system allow you to sign in?	9	5	6	3
6	Does the system allow you to give feedback?	7	4	4	3
7	Which system do you prefer?	7	6	4	3

After deploying proposed system with graphical user interface where all the access and login methods is given in Table 3 in first stage system can allow the patient registration, patient login, doctor registration and login with admin login and the last stage consist with cancer diagnosis, results, report view and doctor feedback.

Table 3. Comparison table of proposed system with existing systems

S.No.	Functions	Proposed System	Existing System 1	Existing System 2	Existing System 3
1	Title	—	Detection of BC using NN	A DSS for BC on invariant feature extraction	System of BC detection using NN for radiologists

2	System Link	—	https://bit.ly/34ozoRP	https://bit.ly/31CWQZJ	https://bit.ly/2Tn5WF
3	Patient Registration	✓	—	—	—
4	Patient Login	✓	—	—	—
5	Doctor Registration	✓	—	—	—
6	Doctor Login	✓	—	—	—
7	Admin Sign in	✓	—	—	—
8	Diagnosis of Cancer	✓	✓	✓	✓
9	Result	✓	✓	✓	✓
10	View Report	✓	—	—	—
11	Patient Feedback	✓	—	—	—
12	Doctors Feedback Online	✓	—	—	—
13	Online Appointment	—	—	—	✓

4. Discussion

Using Convolution neural networks on mammograms, this study developed a strategy for detecting malignant tissues. This BCDS model was trained on the MIAS dataset of mammograms by extracting features from subdivided abnormal classes and comparing them to the normal class. This model correctly classifies the category of mammography images, making it a helpful cancer detection tool for radiologists in the identification of breast cancer. On the original dataset, preprocessing approaches and varying filter sizes in CNN were utilized to reduce noise elements that could affect the overall network's accuracy. It was also mentioned that for effective feature extraction and classification, appropriate segmentation is required. According to the findings of the experiment, the proposed model's overall accuracy is 70%. Deeper structures and novel image processing approaches, as well as more complex images, will be part of our future work to overcome the barrier created by mammograms of dense breasts.

Abbreviations

MIAS	Mammographic image analysis society
ANN	Artificial neural network
WHO	World Health Organization
BC	Breast cancer
SVM	Support vector machine
BCDS	Breast cancer diagnostic system
CNN	Convolutional neural network

OAB	Online appointment book
PCA	Principal component analysis
SURF	Speed up Robust Features
ROI	Region of interest
GUI	Graphical User Interface

5. Conclusion

This research paper utilized a deep learning model to detect breast cancer in mammography images. In the proposed system dataset named Mammographic image analysis society (MIAS) was utilized for the early detection of breast cancer. Convolutional Neural Network (CNN) based system was applied on the mammographic images to accurately detect the cancer. The system generated satisfactory results by diagnosing breast cancer in mammography images with a 70% accuracy rate. As breast cancer is the leading type of cancer among women as well as second leading cause of women's death and its diagnosis at early stages is a difficult task, the proposed system can be deployed to increase the chances of survival through early detection of breast cancer. In future, to overcome the current drawbacks, deeper structures, different image processing methods and more complex images will be used. Deeper structures and novel image processing approaches, as well as more complex images, will be part of our future work to overcome the barrier created by mammograms of dense breasts.

Conflicts of Interest: The Author(s) declare(s) that there is no conflict of interest throughout this study.

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