

## **BREAST CANCER DETECTION USING DEEP LEARNING ALGORITHM**

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**Abstract - Bosom malignant growth is one of the most well-known infections among ladies around the world. It is viewed as one of the main sources of death among ladies. Accordingly, early recognition is important to save lives. Thermography imaging is a viable indicative method which is utilized for bosom disease recognition with the assistance of infrared innovation. In this paper, we propose a completely programmed bosom disease discovery framework. In the first place, U-Net organization is utilized to naturally remove and disconnect the bosom region from the remainder of the body which acts as commotion during the bosom malignant growth identification model. Second, we propose a two-class profound learning model, which is prepared without any preparation for the characterization of ordinary and unusual bosom tissues from warm pictures. Likewise, it is utilized to remove additional qualities from the dataset that is useful in preparing the organization and work on the effectiveness of the characterization cycle. The proposed framework is assessed utilizing genuine information (A benchmark, data set (DMR-IR)) and accomplished exactness = 99.33%, responsiveness = 100 percent and particularity = 98.67%. The proposed framework is supposed to be a useful device for doctors in clinical use.**

### **INTRODUCTION**

Bosom disease is perhaps of the most usually analyzed harm in ladies all over the planet. In 2018, bosom disease came to roughly 15% of enrolled instances of malignant growth connected with passing among ladies. Bosom irregularities can be recognized by self-assessment, doctors, or imaging methods. The best way to guarantee regardless of whether there is malignant growth is biopsy . There are a few bosom imaging methods (for models ultrasound, mammography... and so on), which are at present being utilized for early location of bosom disease. The main and most well known screening methodology is the mammography because of the generally high-exactness, minimal expense, and high perceptibility . Mammograms can give a viable imaging instrument to high precision for bosom disease discovery and arrangement. Notwithstanding, its presentation is known to be frail now and again particularly for patients with thick bosom tissues. Additionally, it might prompt cut off incidental effects connected with ionized radiation for youthful women. Besides, it is known that noticing small size injuries under 2 mm is troublesome utilizing mammograms. These impediments lead to an exorbitant interest in thermography, which is an arising innovation in bosom malignant growth screening. Thermography is a without radiation, minimal expense, non-comprehensive, and painless strategy. Accordingly, it very well may be utilized to recognize beginning phase bosom disease in young ladies and people with thick bosoms.

The primary thought of thermography is that all living bodies produce infrared (IR) above outright zero. A warm infrared camera changes over IR radiation into electrical signs, which are displayed as a thermogram, in the bosom thermography methodology. Subsequently, potential irregularities are underlined and isolated from typical tissue as it has an alternate temperature scale. Bosom thermography enjoys a few upper hands over mammography, including its capacity to work with thick bosom tissues, viability across all age gatherings, and usability for male patients. Thermography is known for being protected (non-ionized radiation), speedy, and prompts early identification of bosom disease. presents the strategy for bosom thermography.

Breast area segmentation is a technique for separating the breast region from other parts of the body in thermal images, and is an important step in any breast cancer detection system. As much as possible, the extracted region must include all breast tissues, ducts, lobules and lymph nodes. Breast segmentation process ranges from a totally manual to a fully automatic. Because of the unique properties of each breast, which make them amorphous, and the lack of clear boundaries in this type of images, most scientific researchers prefer to extract the breast region by using manual or semi-automatic extraction processes.

During the last decades, scientific research has been focused on machine learning methods concerned with the diagnosis of breast cancer using thermography; some researchers concentrate their work on determining the size and location of tumors; but others have been concentrated on characteristics such as acquisition protocols and breast quadrants. Deep learning is one of machine learning methods, which uses multilayer convolutional neural networks (CNN). Deep learning has the ability to automatically extract features from a training dataset. In recent years, scientists have achieved promising results with CNNs for the diagnosis of breast cancer. In the past, the usage of CNNs for the diagnosis of breast cancer with thermal images was not widely used, maybe because of the efficiency of CNNs in comparison with texture or statistical features, or because of the high computational load

. In recent years, CNNs were considered as one of the leading methods for pattern recognition.

The thermal image incorporates superfluous areas as neck, shoulder, chest and other parts of the body which behave as noise during the training in CNN models. However, thermography images are difficult to process due to low-resolution in image spatial domain, it is necessary to extract the breast area from the thermal images which is considered as a critical task as the results of the classification process are highly dependent on segmentation results.

As previously mentioned, breast cancer is considered one of the leading causes of death among women. Therefore, early detection is necessary to save lives. Thermography imaging is an effective diagnostic technique which is used for breast cancer detection with the help of infrared technology, but it is dependent on the radiologist's ability to interpret the thermogram. To the best of knowledge, the prior work has some limitations such as: the

limitation of the dataset, some researches of the related work did not consider segmentation of the breast area before classification or extract the breast area manually, some segmentation models removed parts of the breast, and (4) some researches evaluate their model by calculating the accuracy metric only. However, if the dataset is unbalanced, the model's high accuracy rate does not guarantee its ability to discriminate distinct classes equally. Therefore, a fully automatic breast cancer detection system from thermograms is needed to diagnose the disease.

In this study, we propose a fully automatic breast cancer detection system. First, the U-Net network is utilized to automatically extract and isolate the breast area from the rest of the body in thermograms. Second, we propose a deep learning model, which is trained for the classification of abnormal breast tissues using thermal images. The proposed method consists of three main phases, resizing, breast area segmentation and deep learning model for classification. In the resizing phase, the thermal images are resized to a smaller size to accelerate computation. In the breast area segmentation phase, the breast region is extracted automatically by using the U-Net network. In the deep learning model for classification phase, we proposed a deep learning model based on two-class CNN, which is trained from scratch and used for the classification of normal and abnormal breast tissue.

The main contribution of this paper is as following:

Extracting and isolating the breast area automatically from other parts of thermal images by using CNN (U-Net).

Proposing a deep learning model for the classification of normal and abnormal breast tissues from thermograms

Evaluating the performance of the proposed model using accuracy, sensitivity and specificity.

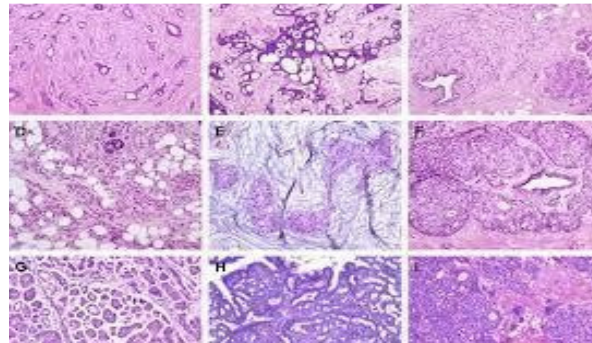
## **DATA ACQUISITION**

We can collect data set manually from hospitals or can use datasets that are previously available, the previously available data sets are the Wisconsin diagnosis breast cancer (WDBC) and Wisconsin in breast cancer database. So, the features are obtained from the digital images of FNA of breast mass Which describes the traits of the cell nuclei.

The data set is collected from the Kaggle website, Data set divided into three category A training set, A validation set, testing set.

This will split our dataset into training, validation, and testing sets in the ratio mentioned above- 80% for training (of that, 10% for validation) and 20% for testing. The original dataset consisted of 162 slide images scanned at 40x. an **imbalance in the class data** with *over 2x* the number of negative data points than positive data points. Preprocessing is the process of image reduce the dimension of image We specify the input

image volume shape to our network where depth is the number of color channels each image contains. The image resizes according to the deep learning layer size of rows and columns of image.



### **CNN FEATURE EXTRACTION**

The network we'll build will be a CNN (Convolutional Neural Network) and call it Cancer Net. This network performs the following operations

Use 3x3 CONV filters Stack these filters on top of each other Perform max-pooling Use depth wise separable convolution (more efficient, takes up less memory) It consists of input layers , convolution layers ,ReLU layer ,max pooling layers for extracting the features of images of the build model. Feature extraction trains the model and builds the model.

### **TRAINING PROCESS**

The training process is implemented for the Adam Adaptive momentum as optimizer for gradient with epochs is implemented training process

it's breast cancer, sorted by size, and the items at the beginning are more likely to be benign, and the ones at the end are more likely to be malignant, then you'll be training on benign data, and testing on malignant, which isn't representative

Based on feature vectors we build the model using the kera'S system.

### **TESTING PROCESS**

The testing process implemented this function. We can split the model with a test set of 30% of the original data set.

The input just specifies the size of the input and is called D (see the code above X\_ train shape).

The dense layer is instead where the real work happens: it takes the input and does a linear transformation to get an output of size 1. The linear transformation we want to apply is the sigmoid activation function so that in output we are in a range of 0 and 1.

loss per iteration, training loss, validating loss is implemented in module Accuracy and sensitivity are analyzed in this.

## **LITERATURE REVIEW**

The majority of efforts related to the diagnosis of breast cancer from thermograms use the web available DMR-IR database. In this section, we will present a review of some studies using the DMR-IR database. Any Computer-Aided Detection (CAD) system for breast cancer detection can be separated into principally three phases: segmentation process, feature extraction and classification. The thermal image incorporates superfluous areas as neck, shoulder, chess and other parts of the body, but during the training in CNN models or during the feature's identification process, this data acts as noise. Therefore, several authors have focused their research on decreasing as much non-relevant information as possible and extracting regions of interest (ROI) instead of identifying patterns in thermograms. Mahmoudzadeh et al. used extended hidden Markov models (EHMM), BayesNet and Random Forest for the optimization of breast segmentation techniques. But, the proposed method can be used only as a first stage in an automatic or semi-automatic system. Also, the algorithm needs to be improved in case of online application. Ali et al. proposed an automatic segmentation method for ROI extraction from breast thermograms based on the normal and abnormal breasts based on statistical and texture features extracted from ROI. But, the presented method has a limitation of the dataset. Also, by this method some lower parts of the breast will be removed. Gaber et al. Proposed an enhanced segmentation method based on both Neutrosophic sets (NS) and optimized Fast Fuzzy c-mean (F-FCM) algorithm. Then, they used different kernel functions of Support Vector Machine (SVM) to detect normal and abnormal breasts. They obtained accuracy = 92.06%, recall = 96.55% and precision = 87.50%. But, the proposed segmentation method was implemented on a limited number of datasets.

## **RESULT AND CONCLUSION**

Breast cancer is one of the most commonly diagnosed malignancies in women around the world. Several researchers have worked on breast cancer segmentation and classification using a variety of imaging techniques.

Thermography imaging is an effective diagnostic approach which is used for breast cancer detection with the help of infrared technology. In this paper, we propose a fully automatic breast cancer detection system. The proposed method is divided into three main stages. First, the thermal images are resized to a smaller size to accelerate computation. Second, the breast region is extracted automatically by using the U-Net network. Third, a deep learning model based on two-class CNN is proposed and trained from scratch for the classification of normal and abnormal breast tissue.

Based on the experimental results, the proposed model achieved accuracy = 99.33%, sensitivity = 100% and specificity = 98.67%. In Table 10, a comparison between the proposed system and other studies based on breast area segmentation and breast cancer detection is performed. Furthermore, Statistical analysis by ANOVA test indicates the viability of the proposed system. In addition, the proposed system is domain-independent, so it has the ability to be applied to various computer vision tasks. In future study, we will investigate deep learning models which can highlight and label defect regions using thermal images.

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