Contour Guided Spatial Attention CNN for Breast Cancer Detection from Thermal Imaging

A thesis submitted in partial fulfilment of the requirement for the

Degree of Master of Engineering

Of

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By

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DECLARATION OF ORIGINALITY AND COMPLIANCE OF ACADEMIC ETHICS

I hereby declare that this thesis entitled "**Contour Guided Spatial Attention CNN for Breast Cancer Detection from Thermal Imaging** " contains literature survey and original research work by the undersigned candidate, as part of his Degree of Master of Engineering in Computer Science & Engineering.

All information in this document has been obtained and presented in accordance with academic rules and ethical conduct.

I also declare that, as required by these rules and conduct, I have fully cited and referenced all materials and results that are not original to this work.

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CHAPTER 1

INTRODUCTION

Cancer is a disease in which aberrant cells multiply uncontrollably and spread nearly everywhere in the body, making it one of the most lethal diseases of the modern era. Generally, human cells increase by the process of growth and division to make new cells according to the body's needs. When cells become old or damaged, they die, and then new cells take their place[4]. If this sequential process of creating new cells from old cells changes down, it creates a cell mass called a tumor. A tumor could be benign or cancerous.
Six types of cancer are most common in India. These are breast cancer, oral cancer, stomach cancer, lung cancer, cervical cancer, and colorectal cancer[6]. Among these, breast cancer is the most common cancer in India. It is commonly found among women of any age but generally 40 and above. The most common symptom of breast cancer is a change in the shape of the breast. According to the 2018 report, breast cancer newly registered cases are 162468, and death cases are 87090 in India[14].
Some factors like obesity, use of alcohol, genetic cause, use of tobacco, increasing age, and reproductive history increase the risk of breast cancer [3].

Different kinds of breast cancer exist, like Ductal Carcinoma, Invasive Lobular, Invasive Carcinoma etc. Below we have discussed a few of the diagnosis methods to determine breast cancer,

- **Histopathology:** Histopathology is the study of tissue which having cancer with a biopsy[31].
- **Thermography:** Thermography records the body's temperature changes which help to determine the cancerous tissue of the breast. It is a fast and cost-effective process[23]. This is why Thermography is used widely in breast cancer detection, and in this work, we have also incorporated thermography images.
- **Biopsy:** The Biopsy is the study of cutting an affected area of the breast to determine whether it is cancer. Due to cutting the affected area, there are chances of infections and bleeding[25].
- **Mammography:** Mammography is the process of study of X-rays image of the breast. The whole process of mammography test takes less than thirty(30) minutes to complete[16], but due to radiation exposure, there are chances of developing cancer[34].

Early detection is crucial for breast cancer patients. It may lead to making survival and improved quality of life. Also, it is the best chance for effective treatment and can help better outcomes. Various works are available to detect breast cancer from thermal images using deep learning. Deep learning is a subset of AI(artificial intelligence) that uses ML(machine learning) techniques to analyze patterns and predict from large data sets. We will discuss how the deep learning technique applies to cancer diagnosis. A deep neural network is several densely interconnected neurons managed into sequential layers. Within each layer, every single neuron is connected to other neurons from which it receives the data. Training samples and ground truths are fed to the network's input layer, and then the information is travelled to all hidden layers via each neuron. Information is added, divided, and subtracted millions of times before reaching the output layer. In supervised deep learning, every pair of labels and training sample is fed to the neural network while the threshold and its weights are adjusted to get the provided label to make an accurate prediction[33]. In this work, we have also used a Convolutional Neural Network(CNN) to detect breast cancer from thermal images. Most of the works in this field utilized only the raw thermal data for training their networks, but sometimes the raw thermal data can contain noise and redundant information. To overcome this, we use various pre-processing techniques on the raw data to enhance the relative important information, which helps in better prediction. Since the shape of the breast changes due to cancer, a significant portion of the upper half of each thermal image is useless. This is one of our key observations. We have utilized this fact and used a contour guided Spatial Attention Module in the CNN to better focus on the relevant areas. To summarize, the contributions in this work are as follows

- we have incorporated a few pre-processing techniques to enhance the image to extract the contour mask having the ROI,
- we have proposed a custom CNN, which consists of very few parameters than other traditionally used CNNs like ResNet, DenseNet, InceptionNet etc.,
- we have proposed a Contour guided Spatial Attention Module in the CNN to focus on more prominent areas for better predictions.

In the next section, we have discussed various related works that have been done in this domain.

CHAPTER 2

LITERATURE SURVEY

Many researchers utilized various computer vision-based processes for breast cancer classification. Few are focused on segmentation, followed by feature extraction, and some of them just extracted features from raw datasets. Many researchers used pre-processing in a few studies to highlight infected parts and improve the enhancement of the images for better feature extraction. We have briefly discussed some works below.

Chatterjee et al.[13] performed transfer learning to avoid overfitting a dataset. They proposed a modified version of the Dragonfly Algorithm to reduce the feature dimension. Afterwards, meta-heuristic optimization and a deep neural network were combined to determine breast cancer.

Mahesh et al. [20] performed pre-processing to enhance the quality of image data through data normalization, data cleaning technique, and data transformation. They have performed feature scaling and selection in this methodology. Later, pre-trained models have developed for breast cancer classification.

Aljuaid et al. [7] introduced breast cancer classification automatic diagnosis. They collected the dataset from BreakHis and performed normalization, enhancement and data augmentation. Later, They modified the pre-define DNNs Training model for breast cancer classification and achieved impressive outcomes.

Krawczyk et al. [18] extract the region of interest(ROI) from the breast thermogram to use frontal and lateral views of the breasts and then discriminant between the healthy and malignant cases.

Saber et al. [27] performed minimizing training time and extracted only affected breast images. They used histogram equalization, noise reduction, and morphological operation to improve affected region detection. Resolve the overfitting problem. Later, They performed transfer learning for breast cancer classification.

Viswanatha Reddy Allugunti [8] performed pre-processing on the dataset to improve image quality. They enhance the CNN classification method in addition to SVM and Random Forest for comparative analysis. Later, graphical evaluation to assess how well the system functions.

Michael et al. [22] collected the breast dataset from a local hospital. They created a mask of images to detect the outline of an image. They introduced ML classifiers, including SVM(support vector machine), k-NN(k-nearest neighbour), random forest(RF), XGBoost, and LightGBM. These ML classifiers were optimized using a tree-structured parzen estimator, and the image dataset has divided using 10-fold cross-validation.

Some researchers used the hybrid intelligent technique to extract the feature, use different hybrid classifiers, and classify breast thermograms. In [15], the authors used the inception v3 as the base classifier model on the Database of Mastology Research database with 1065 thermal images. They split the dataset into 80,20 per cent for training and validation datasets. They added an SVM machine at the end of the classification's CNN network model, fixed the LR(Learning Rate) to 0.0001, and ran the epoch to 15. The authors did not mention the accuracy rate but declared the percentage of the presence of breast cancer in the breast[21].

The authors in [17] used the decision tree classifier and machine learning-based classical approach to distinguish between cancerous and benign cases. A small dataset of 60 thermograms achieved sensitivity and accuracy of 86.70, 93.40 per cent.

Above mentioned techniques, typically, researchers introduce transfer learning as feature extraction. However, most did not pay attention to enhancing thermal images, which we feel is essential for accurate predictions. In this work, we have used some pre-processing on the thermal images and proposed a custom CNN with a contour guided spatial attention framework for breast cancer classification.

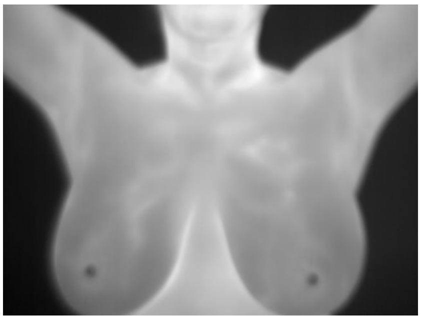
CHAPTER 3

DATASET DESCRIPTION AND PRE-PROCESSING

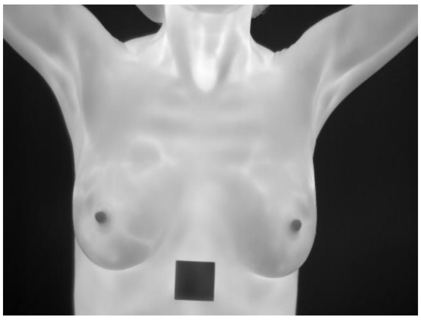
The detailed description of the used dataset and some pre-processing techniques used in this work are discussed below.

3.1 Dataset

The DMR(Database for Mastology Research) dataset[2] is a publicly available collection of thermal images which can be downloaded from https://visual.ic.uff.br/dmi/. For this study, We have considered the total number of 2015 images. Out of which 1550 are healthy and 665 are sick images. Among the total 2015 images, 1411 is in the '.txt' format, and 604 is the original '.png' format. Breast images had captured using an infrared camera with a fixed temperature of 0.04 degrees centigrade. Each images has the dimension of 640 by 480 pixels[32]. Few of the original images from the DMR dataset has shown in the following.

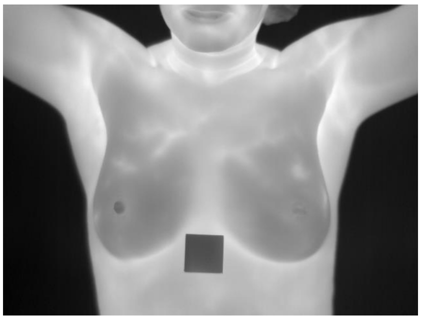


(a)



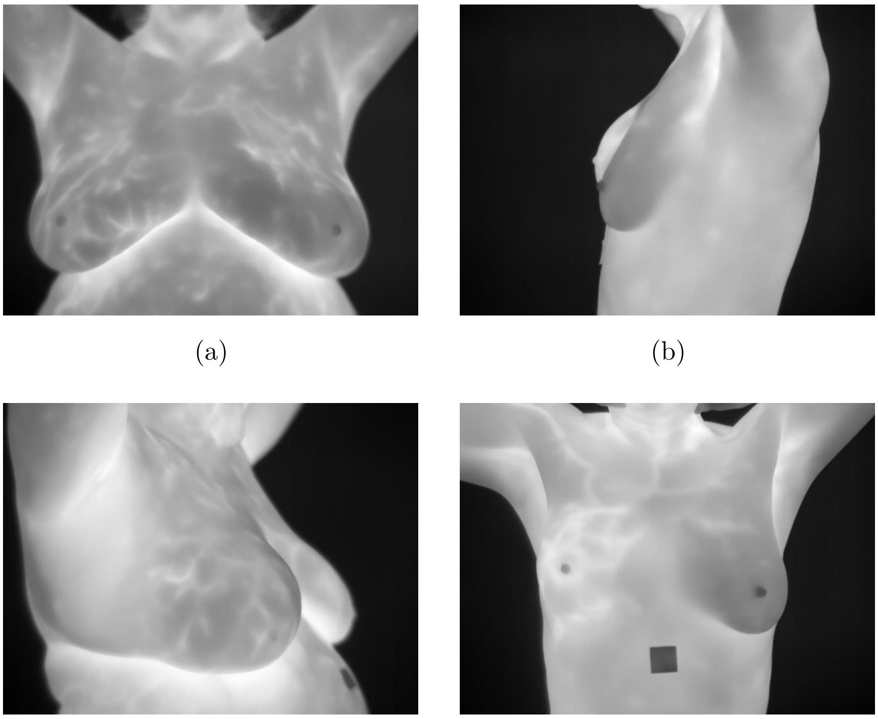
(b)

(c)



(d)

Figure 3.1: Displayed healthy images from DMR dataset



(a) (b) (c) (d)

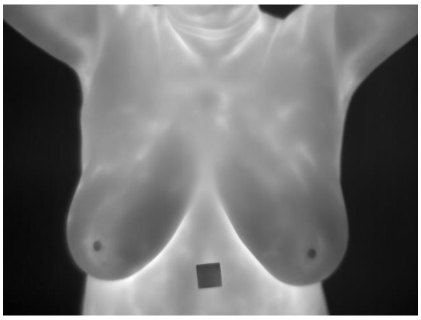
Figure 3.2: Displayed sick images from DMR dataset

3.2 Data Pre-Processing

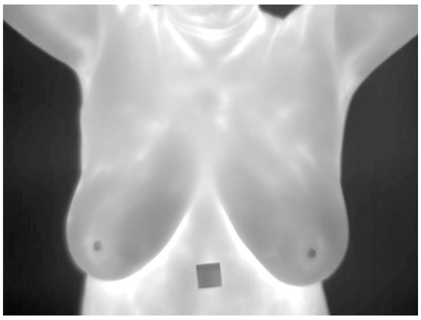
Pre-processing an image can helps to enhance distinguishable features from the raw data which can further affect models performance positively. We have performed pre-processing on image to remove various unwanted outliers from the dataset and also, to enhance the quality of images. These techniques are discussed below.

3.2.1 Contrast Adjustment of the Image

Contrast adjustment of images is a crucial factor in improving image quality. Increasing the contrast of images creates the difference between the light and dark areas of the picture. Contrast adjustment means that dark parts adjust the lightest section of the image, while brightness adjusts the dark parts[10]. We have calculated the optimal contrasting threshold value empirically by observing the visual features of the images.



(a) Before Contrast Adjustment



(b) After Contrast Adjustment

Figure 3.3: Contrast Adjustment of the Image

3.2.2 Convert RGB Image to Grayscale Image

Conversion of RGB images to the grayscale image is another important image pre-processing technique. The importance behind the transformation of RGB image to a grayscale image is color complexity, easier visualization, noise reduction, speed, and code complexity[12]. After contrast enhancement of the image, We have converted that enhanced RGB image to a grayscale image for the edge detection operation. Generally, Three standard methods are there to convert an RGB image into a grayscale image: The lightness Method, the Average Method etc. We have briefly discussed these methods below.

Lightness Method

The lightness method is a straightforward technique for converting RGB into Greyscale. It takes the average of the highest and lowest value. This method's weakness is that all the RGB image's middle components are not used. The intensity value of a grayscale image is calculated as follows[9]:

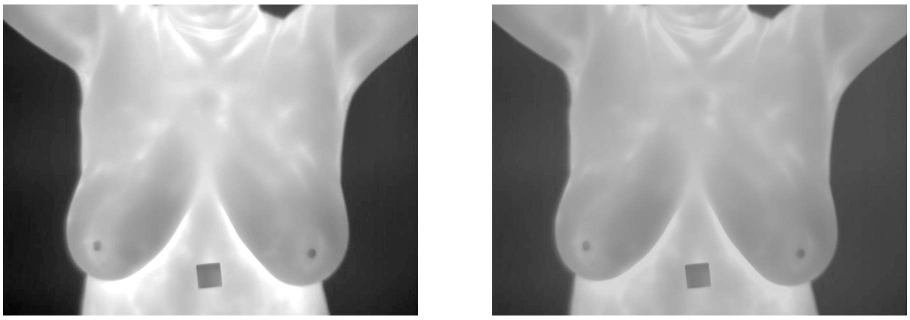
$$grayscale = \frac{\min(R, G, B) + \max(R, G, B)}{3}$$

Average Method

This method takes the average value of three components as the grayscale value. Because it is an RGB image, We need to calculate the average value of R, G, and B on every pixel location to create a grayscale image. It is problematic because it assigns equal weight to every component[9]. The intensity value of a grayscale image is calculated as follows:

$$grayscale = \frac{(R_{(x,y)} + G_{(x,y)} + B_{(x,y)})}{3}$$

where $R_{(x,y)}, G_{(x,y)}$ and $B_{(x,y)}$ are the intensity of Red, Green and Blue channels at pixel location (x, y) in the RGB image. In this work, we have considered the average method.



(a) Contrast Adjusted Image in RGB

(b) Grayscale Image

Figure 3.4: RGB Image to Grayscale Image Conversion

3.2.3 Create Mask for ROI

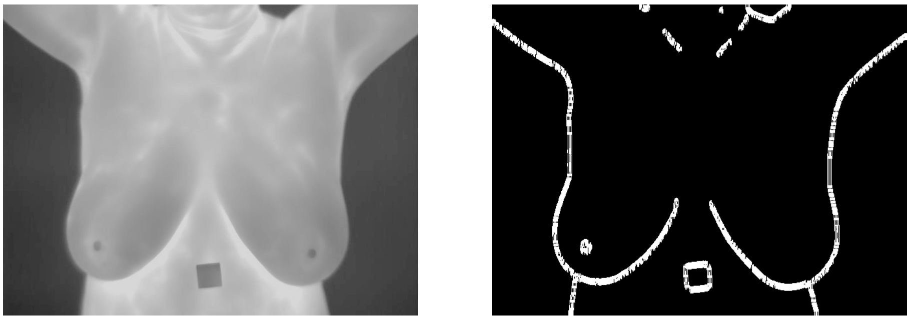
We have created a mask to understand the region of interest better. For this purpose, the Canny Edge Detector is used on these grayscale images.

Canny Edge Detector

The collection of many connected components simultaneously forms an edge between two disjoint regions. The canny edge detector is a popular technique that extracts feasible information to find the boundaries of an object[5]. John F. Canny invented it in 1986. It takes a grayscale image as input to detect the boundaries of an object.

Algorithm 1 Canny Edge Detection Algorithm

1: Apply a gaussian filter to remove the noise to smooth the image.
2: Find intensity gradients.
3: Apply non-maximum suppression to edge detection.
4: Apply double threshold to determine potential edges.
5: Track edge by hysteresis by suppressing all the other weak and not connected to potential edges boundaries.



(a) Grayscale Image

(b) Mask Created from Grayscale Image

Figure 3.5: Mask Generated from Grayscale Image

3.2.4 Morphological Operations

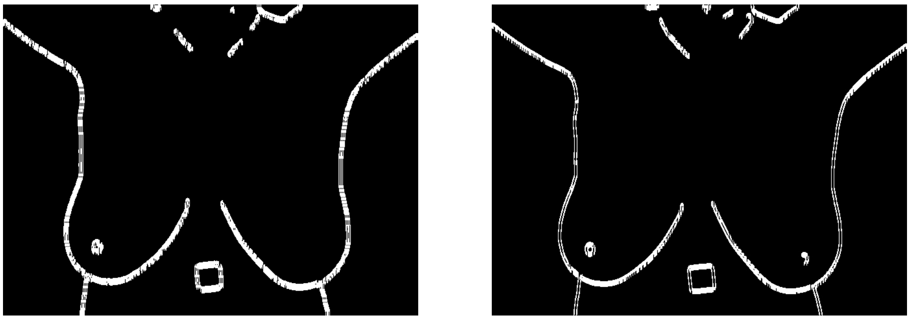
Morphological Operations are a set of image processing operations that procedure digital images based on their shapes. Each image pixel in a morphological operation corresponds to the value of another pixel in its neighbourhood. It is sensitive to specific shapes in the input image[28]. Morphological operations use a structuring element to create an output image of the same size as the input image. Various types of morphological operations are discussed below.

Erosion

In this process, we take a structural element or kernel and traverse it all over the input image. During this, we fix the centre point of the kernel on each pixel. If the fixed centre and the neighbourhood points of the kernel match with the corresponding pixels in the image, we consider the pixel under the fixed centre point as one.

Dilation

This is somewhat the opposite of Erosion. In this process, we take a structural element or kernel and traverse it all over the input image, like Erosion. However, If the fixed centre and one of the neighbourhood points match the corresponding pixels in the image, we consider the pixel under the fixed centre point as one.



(a) Before Morphological Operations (b) After Morphological Operations

Figure 3.6: Effects after Performing Morphological Operations

3.2.5 Binarization

One of the most significant features of binarization is converting the greyscale images with values ranging from 0 and 1 (black and white). This technique provides precise and sharper contours of the images and can reduce background noise also.

Algorithm 2 Binarization Algorithm

1: Convert the RGB image to Grayscale image.
2: Apply a gaussian filter to remove the noise to smooth the mask image.
3: Find intensity gradients.
4: Identify threshold based on a histogram.
5: Converted binary image.

The algorithm for the pre-processing is presented in Algorithm 3 and the overall flowchart is shown in Figure 3.7.

Algorithm 3 Image Pre-Processing

1: Read RGB breast thermal input image I
2: Apply contrast adjustment on I
3: Convert RGB image(I) into grayscale image(M)
4: Perform Morphological operation(Erosion) on M and save the output image as M_1
5: Subtract M_1 from G to reduce noise and save the results in M_2
6: Do Morphological operation(Dilation) on M and save the output in M_3
7: Add M_2 and M_3 and save the result in M_4
8: Perform Binarization on M_4 images
9: Save the resultant image after performing the Binarization method

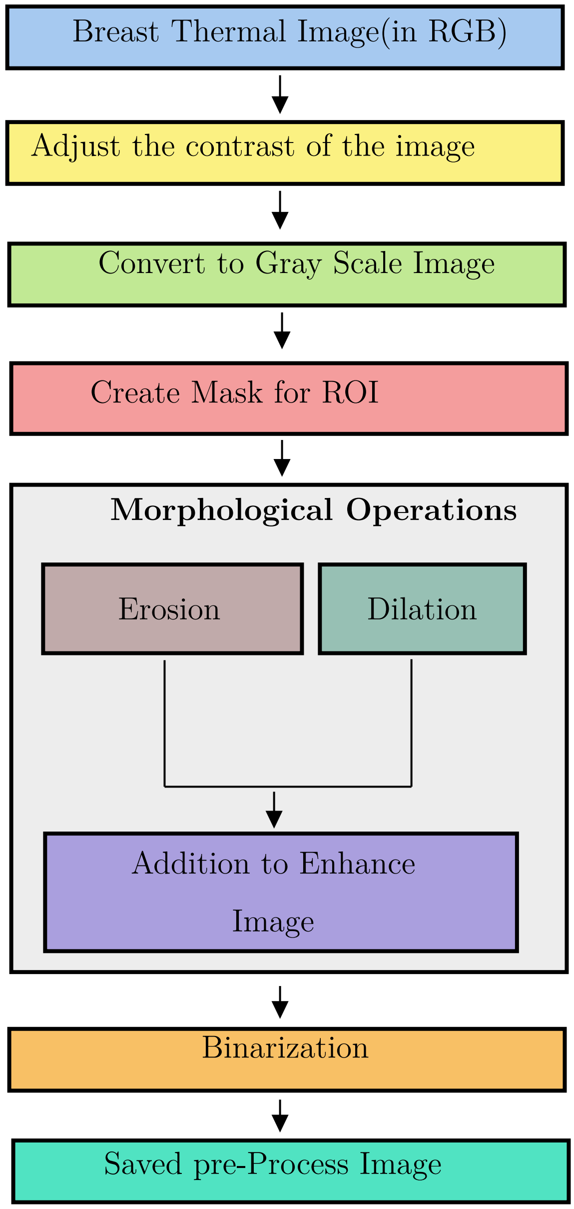


Figure 3.7: Image pre-processing flowchart

CHAPTER 4

METHODOLOGY

Deep Learning is structured learning-based architecture. Different architectures of deep learning employ deep neural networks, which are applicable in many areas like image processing, audio recognition, machine translation, language processing etc. [8]. In this work, we have developed a custom Convolutional Neural Network for the Breast Cancer detection task. In the next section, we discuss our proposed network architecture in detail.

4.1 Proposed CNN Architecture

The CNN is created by stacking different layers, i.e., Input, Convolutional, Batch Normalization, Max-Pooling, Dropout Layers, Fully Connected, and Non-Linear activation layers(RelU). We discuss each of these in detail below.

4.1.1 Input Layer

The input layer takes the input as a tensor and feeds it to the deeper layers in the network.

4.1.2 Convolutional Layer

Convolutional Layer is the main block of any CNN. It contains three arguments, the first argument is used for the filter size, and the second argument provides the features maps. The padding layer ensures that output size and input size are the same. Our network consists of three convolutional layers with filter size 5x5, which are applied to the input data to determine the activation map. In this way, layers output provides stacking of activation maps.

4.1.3 Batch Normalization Layer

The normalization layer ensures by optimizing activation and gradients through a neural network.

4.1.4 ReLU

ReLU means rectified linear unit. It applies as an activation function on an input tensor without changing any information.

4.1.5 Max Pooling

Max Pooling performs to retain the most prominent features of the previous feature map. It removes the remaining redundant information and results in a reduced feature map. We have used a 2x2 kernel in our network to retain the most dominant feature.

4.1.6 Dropout Layer

The dropout layer drops out individual nodes from the net. It applies to avoid overfitting, which means it allows a network to learn more features efficiently. By several experiments, 0.40 per cent is the best for our modified neural network.

4.1.7 Fully Connected Layer

This layer learns from the previous layers across the network to make a prediction. First, the max pooling and convolutional layer are flattened and fed to the fully connected layer.

4.1.8 Classification Layer

Classification is the last layer of the network. A softmax function is used at the end of the network to obtain the probability distribution across the classes of each input image.

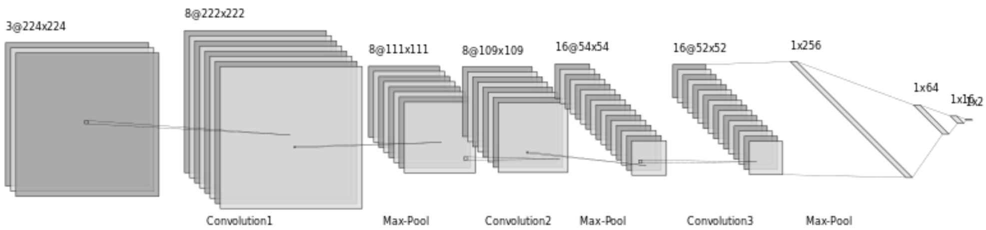


Figure 4.1: our proposed CNN architecture

4.2 Spatial Attention Module

4.2.1 Attention Mechanism

Attention mechanisms are a deep learning technique to determine additional concentration on a specific component. The model generally concentrates on one of the particular components within the network that manages the relationships within the input, named self-attention, and the relationships between output and input called general- attention. The main preface of the attention models is to reduce complicated tasks and focus on specific areas. These models work within neural networks, which are also a network with the same architecture [1]. It focuses on some particular region at a time and neglects the rest.

4.2.2 Contour guide Spatial Attention Module

The primary motivation for this part comes from the observation that a breast's shape changes when there is cancer. We can get the shapes from images with an edge detector. We have used a canny edge detector in the pre-processing phase to detect these contours. Now the spatial attention from these contours can force the network to look for the changes in shapes, making it better at prediction. In this process, we first pass masked images as input to a localization network, which regresses the transformation parameters θ. That transformation parameter θ is never calculated explicitly from the input feature dataset; instead, the network automatically learns the spatial transformation that enhances the global accuracy. The regular spatial grid G over the output feature map is transformed to the sampling grid T(G), which is applied to the input feature map(masked image), which produces the final output feature map.

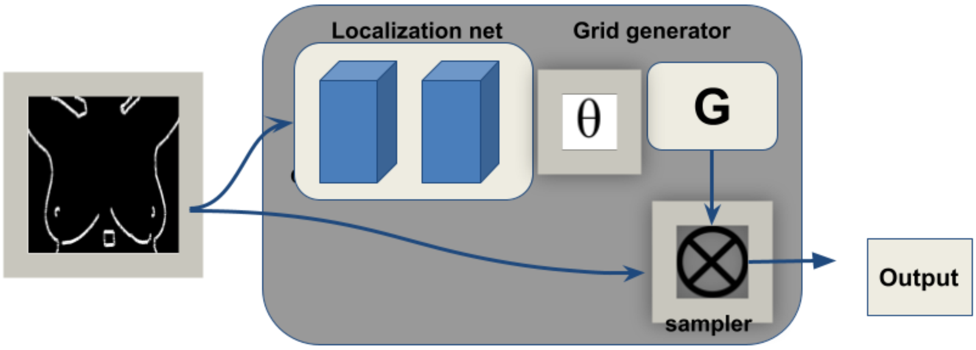


Figure 4.2: Spatial Attention architecture

These output feature maps are considered as spatial attention and multiplied with the original images, and fed to the CNN for training. In Figure 4.3 we have shown the whole proposed architecture.

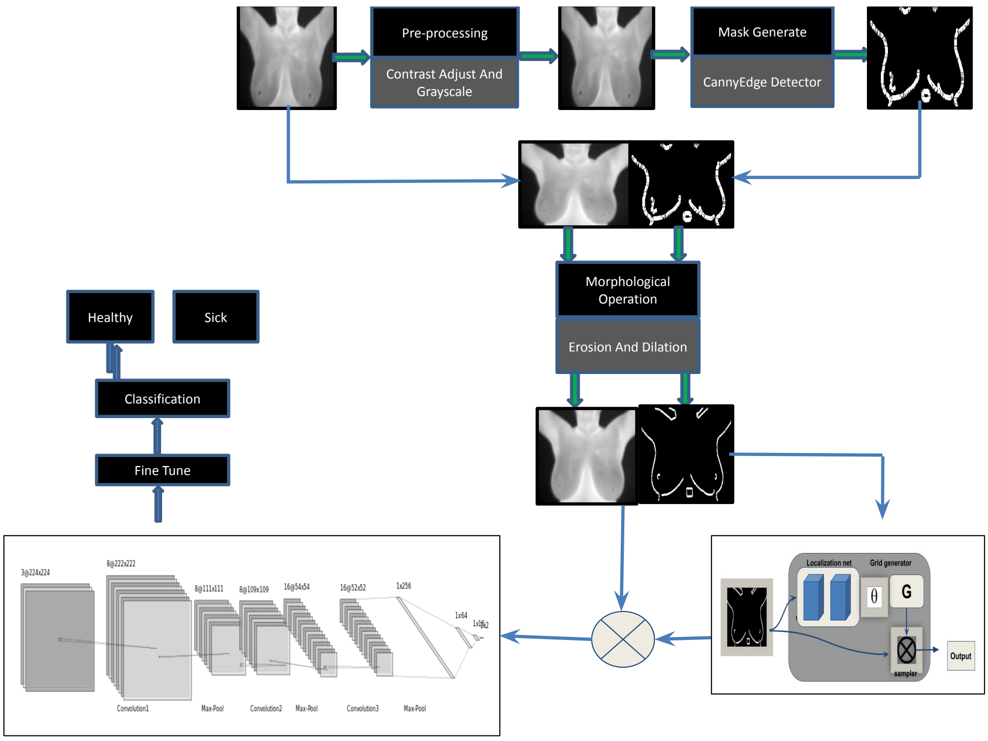


Figure 4.3: Methodologies of whole process architecture

CHAPTER 5

EXPERIMENTS

5.1 Experimental Setup:

We divide the whole dataset into training, testing and validation with a ratio of 70:15:15. All the data has been pre-processed with the methods described in chapter 3 and resized to 224x224 before feeding into the network. We performed the whole experiment in two folds, one with only thermal images and another with thermal and generated masked images. The details of each investigation are described below.

5.1.1 Only Thermal Images

Here, we have taken only original thermal images for consideration. The cross-entropy loss and SGD are used as loss function and the optimizer for this part. We manipulated other hyperparameters, such as batch size, learning rate, and epochs, and noted the overall performances of the network. A few of them are mentioned below. (i) In the first experiment, We used a batch size of

4, epochs at 10, and a learning rate of 0.0001. After completing training, We got 80% validation accuracy and 79% test accuracy with five convolutional layers. (ii) Next, we experimented with a batch size of 8, epochs at 50, and a learning rate of 0.0001. We got an accuracy of validation of 82%. (iii) When training with a batch size of 16, epochs at 100, and a learning rate of 0.0003. We achieved a validation accuracy of 84%.

5.1.2 Original Thermal Images with Masked Images

Here also, a similar approach is taken for the experiment, but instead of a single image, we have given a concatenated image (original + generated masked) as input. A few experiments are discussed here (i) In the first experiment, We used a batch size of 4, epochs at 10, and a learning rate of 0.0001. After the completion of training, We got 87% validation accuracy and 87% test accuracy with five convolutional layers. (ii) Next, we experimented with a batch size of 8, epochs at 50, and a learning rate of 0.0001. Here, we got a validation accuracy of 88%. (iii) When training with a batch size of 16, epochs at 100, and a learning rate of 0.0003. We have achieved a validation accuracy of 93%. This significant improvement is due to the extra information provided by the masked image.

5.1.3 Experiments With Spatial Attention

In this case, we have taken both the original and masked image for input. However, instead of a concatenation, we have fed the masked images into the previously discussed attention module. This attention mask is concatenated with the original images and fed into the network as input. Here, we used the Adam optimization algorithm and multiclass cross entropy function as the optimizer and the loss function, respectively. The rest of the procedure is similar to the previous experiments discussed below. (i) In the first experiment, a batch size of 8, epochs at 50, and a learning rate of 0.0001 are used. After training, We achieved a testing accuracy of 92%. (ii) For the second experiment, We have taken a batch size of 16, epochs at 100, and a learning rate of 0.0002. We got an accuracy of 94%. (iii) In the third experiment, We performed with a batch size of 16, a learning rate of 0.0003, a dropout of 0.40, and epochs at 100. After training, we achieved noticeable accuracy of 98.011%.

5.2 Performance Metrics

Let's understand the different parts of a confusion matrix in terms of analogy.

- True Positive: I predicted positive, and it's true. Suppose I said that the man is corona positive, and it's true.
- True Negative: I predicted negative, and it's true. Suppose I said that the woman is corona negative, and it's true.
- False Positive: I predicted positive, and it's false. Suppose I said that the woman is corona positive and she is not.
- False Negative: I predicted negative, and it's false. Suppose I said that the man is corona negative and he is not.

With the above analogy, we can define Accuracy, Precision, Recall and the F1 score.

5.2.1 Accuracy

It represents the ratio of correctly classified corona patients $(TP + TN)$ to

the total number of corona patients.
Accuracy = $(TP + TN)/(TP + TN + FP + FN)$

5.2.2 Precision

Precision is the ratio of correctly identified patients with corona disease (TP) to the total number of patients predicted to have corona $(TP + FP)$.
precision = $(TP)/(TP + FP)$

5.2.3 Sensitivity

Sensitivity or Recall metric is the ratio of correctly classified corona positive to the total patients with the disease.
Sensitivity= $(TP)/(TP + FN)$

5.2.4 Specificity

Specificity metric is the ratio of wrongly classified corona positive to the sum of TN and FP.
Specificity= $(TN)/(TN + FP)$

5.2.5 F1 Score

F1 score is defined below.
F1 Score = $2 * (precision * Recall)/(precision + Recall)$

5.2.6 Confusion Matrix

A confusion matrix represents the performance of a classification model. It summarizes and visualizes the performance of a classification algorithm. The confusion matrix consists of four basic characteristics, namely True Positive(TP), True Negative(TN), False Positive(FP), and False Negative(FN).

CHAPTER 6

RESULTS AND DISCUSSION

Experiments have been performed on a desktop core i5 processor of 2.0GHz, 4GB of Nvidia-GForce Graphics, and 8GB of RAM. Table 6.1 shows the count of ”Sick” and ”Healthy” images from the dataset.

Label	**Count**
Healthy	1550
Sick	665

Table 6.1: Data Table

Simulation parameters are shown below that have been used in our network architecture

S.No	Parameter	Value
1.	Input Sample size	640x480
2.	Batch size	16
3.	Learning Rate	0.0003
4.	Pooling 'maxpool_1' 'Maxpool_2'	2x2
5.	Batch Normalization 'batchnorm_1' 'batchnorm_2'	8 channel 32 channel
6.	Stride	1
7.	Kernel	5x5
8.	Optimization Algorithm	Adam

Figure 6.1: Simulation Parameters Tabels

6.1 Training and Validation loss

The training loss is an error that assesses how the model fits the training data. Generally, the training loss has calculated by taking the sum of errors of each sample in the training set.

On the other hand, The validation loss is an error that assesses how the model fits the validation data. The validation set is a part of the dataset used to validate the deep learning model and helps overcome the overfitting problem. Generally, the validation loss is calculated by taking each sample's sum of errors in the validation set[11].

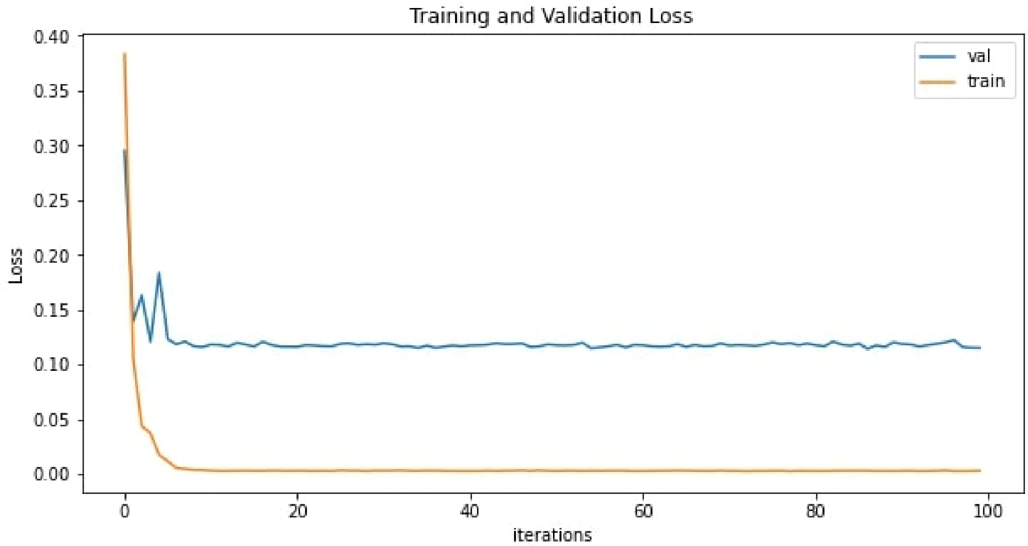


Figure 6.2: Training loss and validation curve of the final experiment with our proposed method.

The above training loss and validation loss graph shows that the training loss curve is below the validation loss. Usually, the training loss should be below the validation loss. The blue curve indicates the validation loss and the yellow curve indicates training loss.

6.2 Results of Performance Metrics

6.2.1 Confusion Matrix

A confusion matrix represents the performance of a classification model.

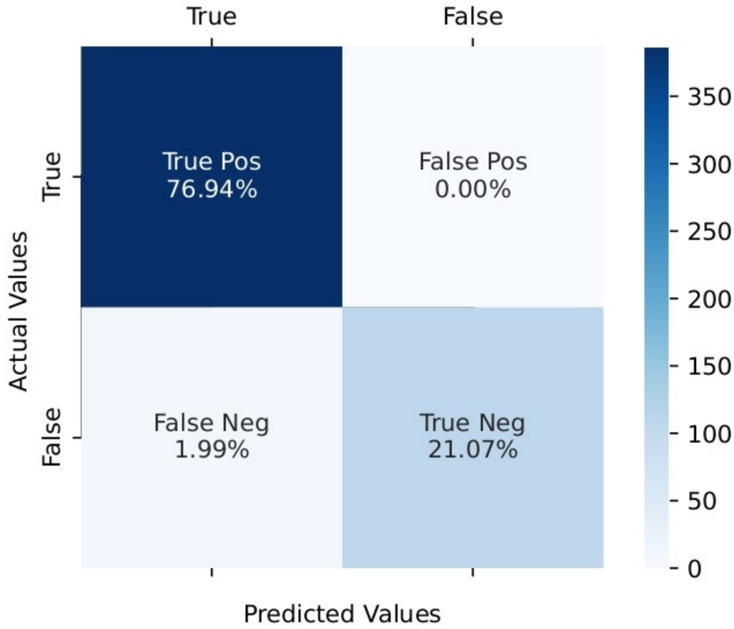


Figure 6.3: The confusion matrix of our proposed model's performance in the final experiment

In the final experiment (i.e. the batch size of 16, a learning rate of 0.0003, a dropout of 0.40, and epochs at 100.), our model achieves 76.94% true positive, 21.07% is a true negative, and 1.99% is a false negative. Other metrics are also given by Accuracy: 98.011%, Precision: 100%, Sensitivity: 91.379%, Specificity: 100%, F1score: 95.495%.

In Table 6.2, we have shown the performances of different experimental protocols described in Chapter 5. Here, M1 indicates the experiments performed with only Thermal images, M2 indicates the experiments performed with only masked images, and M3 indicates the experiments performed with Thermal and generated masked images. Finally, M4 represents the experiment with The original images and the spatial attention module on the masked images.

Model	Accuracy	Precision	Sensitivity	Specificity	F1 score
M1	0.84	0.85246	0.80457	0.88942	0.86376
M2	0.87	0.86278	0.85467	0.90482	0.87512
M3	0.93	0.97658	0.88621	0.96271	0.95307
M4	0.98011	1.0	0.9379	1.0	0.95495

Table 6.2: Figure based on several experiments on dataset

In the next Table 6.3, we have compared our results with other works which are discussed earlier.

Model	Accuracy	Precision	Sensitivity	Specificity	F1 score
Paramanik et al.[26]	0.8940	-	-	-	-
Mishra et al.[24]	0.9580	-	0.995	0.763	-
Sanchcz-Caucc et al.[29]	0.97	-	0.83	1.0	-
Zuluaga-Gaomez et al.[35]	0.92	0.94	0.90	-	0.92
Satish et al.[30]	0.91	-	0.8723	0.9434	-
Lessa & Maurengoni[19]	0.9814	0.9454	0.9433	-	0.9306
Mahesh et al.[20]	0.87	-	0.83	0.85	-
Ours	0.98011	1.0	0.91379	1.0	0.95495

Table 6.3: Comparison our models with other literature

CHAPTER 7

CONCLUSIONS AND FUTURE WORK

We proposed a Contour guided Spatial Attention based CNN for breast cancer detection from thermal images of the DMR-IR dataset. Here, we have taken both the original and pre-processed masked images for the experiment. Our proposed CNN performs way better when we use both the original and masked image together as the input rather than the only original images. However, incorporating spatial attention to the masked images provides relevant information to the CNN, which helps it to make better predictions. This Countour guided spatial attention based CNN achieves 98.011% testing accuracy, which is way better than some of the earlier work done in this dataset. Here are some aspects that we will focus on in the future-

(i) Evaluation of other datasets related to this domain to demonstrate the superiority of the model.

(ii) Along with the proposed model, the impact of the combined channel and spatial attention model will be examined.

(iii) Analyze the various uncertainties present with this approach and model them.

(iv) Build a superior CNN model based on the Inception module or Visual transformer.

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