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Predicting of Breast Cancer using Grad-CAM and Bounding Box

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ABSTRACT:
Soft Computing, Machine Learning and Artificial Intelligence tools can save the lives through improved efficiency and diagnostic accuracy. For accurate diagnosis image analysis is the best approach. For this approach Feature extraction is a critical step in predicting any diagnosis. It involves identifying and extracting the most relevant features from the image which can then be used to train soft computing models for accurate prediction of diagnosis. Soft Computing with processing the medical images is an effective method to knob suspicions inherent in attained image data. To lessen number of people lost to cancer, early diagnosis and treatment are paramount. In worldwide Breast Cancer is a common kind of cancer. As per WHO (World Health Organisation) 2.3 million new diagnoses and 685,000 demises in 2020 alone. The most cases of breast cancer are found in female. Uncontrolled progress of breast cells is the root cause of breast cancer. Breast cancer can take many forms. What form of breast cancer is in patient is determined by which breast cells become malignant. In this article, the breast cancer tumor is predicted with a feature extraction technique: Gradient-Weighted Class Activation Mapping (Grad-CAM) and Bounding Box (BB) along with Convolutional Neural Network (CNN) for accurate results in predicting the tumor and its location.

1. Introduction

More over one in ten new cases of cancer each year are identified as breast cancer, makes it as most occurring cancer in women. It's the second most common type of cancer that kill women. Milk fabricated glands are situated in breast tissue just in front of chest wall. The pectoralis muscle supports the breasts and ligaments join the breasts to the chest wall. There are fifteen to twenty lobes in each breast, arranged in a ring. The quantity of fat that sits on a woman's breast lobes is what gives them their shape and size. Lobules, which contains glands that produce milk and react to hormone stimulus to produce milk, combine to form each lobe. Cancer of the breast always progresses in silence. Regular screenings are where the vast majority of patients learn they have a disease. Some patients present with common symptoms like discharge from the nipple or change in the size or form of their breasts. On the other side Mastalgia is quite prevalent. Breast cancer can only diagnose by a combination of a thorough imaging tests (mainly mammography), physical examination and a tissue sample. Early detection increases chance of survival. Poor prognosis is associated with the tumor's tendency to metastasize via lymphatic and haematological pathways [1]. This helps to shed light on and highlight the importance of breast cancer selection initiatives [2][3].

Therefore, precise segmentation of medical pictures is crucial for improved treatment planning [4]. Segmenting an image is the process of breaking it down into its component pieces or individual objects [5]. These objects are then put to use in the fields of image analysis and image processing. Soft computing devours played a major role in the detection and diagnosis of breast cancer illnesses early analytically with enhanced effectiveness and appropriate accuracy using methodologies and relevant attributes reference value. Soft computing is a collection of methodologies that enable flexible information processing. In contrast, soft computing is a

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contemporary strategy built on approximation, ambiguity and adaptability. Since efficient, accurate medical image segmentation requires the employment of both soft computing and hard computing approaches.

In the previous study [25], the classification of data is done by applying Convolution Neural Network (CNN) for analysing and identifying the breast cancer tumor. For the analysis CNN is mainly used because it is a most popular and another kind of neural network that can discover key info with time series and image data. For this aim, it is extremely valued for image connected tasks that can learn from raw pixel data without requiring any manual feature engineering or pre-processing.
By applying CNN on the 2023 RSNA Breast Cancer dataset, analysed how best CNN algorithm is for analysis is identified with accuracy and also tried to analyse at what age breast cancer is generally happened in women.

Feature extraction is a critical step in predicting breast cancer using image processing. It involves identifying and extracting the most relevant features from the image which can be used to train machine learning techniques for accurate prediction of breast cancer. This method can guide medical interventions such as surgical planning and medication planning, leading to better patient outcomes.

In this article, the breast cancer tumor is predicted with a feature extraction technique: Gradient-Weighted Class Activation Mapping (Grad-CAM) and Bounding Box (BB) along with CNN for accurate results in predicting the tumor and its location.

Here is how the rest of artcle is structured: The second part discusses the literature review, the third the technique, the fourth the experimental analysis, and the last the conclusion.

2. Literature Review

Using ultrasound pictures, Eroglu Y [17] proposed a CNN system based on a hybrid architecture by extracting features from MobilenetV2, Alexnet and Resnet50 concatenating them and picking the best features using the mRMR features selection approach. In order to classify data, this system used machine learning techniques such as Support Vector Machines (SVMs) and K-Nearest Neighbours (K-NNs). The end result was a success percentage of 95.6%. In [18], the breast US images were segmented using an image segmentation method, and then the BC-related sub-regions were automatically detected using an object identification method that employed feature extraction, selection, and classification techniques. Cropping an area of interest, enhancing it with filters and clustering algorithms, extracting features, and classifying with a neural network and a k-NN classifier are all steps in a method proposed in [19] for segmenting BC images using semantic classification and patch merging.

In order to detect and localise BC in dynamic contrast-enhanced MRI data, Zhou J. et al. [20] present a 3D deep CNN using a weakly supervised technique and achieve an accuracy of 83.7%. To classify MRI images of tumours as malignant or benign, [21] developed a multi-layer convolutional neural network (CNN) using pixel information and dynamic data augmentation. The network obtained an accuracy of up to 98.33%.

On the DDSM dataset, the authors of [22] Using InceptionV3 and ResNet50, two pre-trained CNN models, they were able to identify benign from malignant tumours in mammograms. To make up for the lack of data, researchers utilised pre-processing, data augmentation, and transfer learning techniques. Compared to InceptionV3's 79.6% accuracy, ResNet50's was 85.7%. The authors of [23] used a CNN model that takes into account data from a number of different MLO (Medio Lateral Oblique) and CC (Cranio Caudal) pictures. Accuracy of 82.02% was achieved using multi-scale features and a penalty term on the DDSM dataset. A method for detecting BC in the CBIS-DDSM image collection was proposed by Ridhi Hela et al. in [24]. After the images were processed many CNN models were utilised to draw out specific characteristics.

Class Activation Mapping (CAM) is a method recently described by Zhou et al. [15] for finding discriminative regions employed by a subset of Convolutional Neural Networks (CNNs) used for classification of image do not have any layers are fully-connected. In kernel, this effort compromises complexity of model and performance in exchange for new insight into model's inner workings. Instead, we avoid the accuracy vs. interpretability trade-off by rendering current state-of-the-art interpretable deep models deprived of changing their design.

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In order to combine boxes during iterative localization, MR-CNN [8] is initially proposed. To discover the connection between bounding boxes, the authors of [9] propose a relation network. The IoU among expected and bounding box ground-truth has recently been proposed for learning via Intersection over Union network (IoU-Net) [10]. The detection boxes are then subjected to Intersection over Union Non-Maximal Suppression (IoU-NMS), with the learned IoU serving as a guide. In contrast to IoU-Net, we advocate for a probabilistic approach to learning the localization variance. It allows us to learn, independently of IoU, the alterations for the four coordinates for bounding box prediction.

3. Methodology

The main objective of this article is to present the prediction of exact location of breast cancer tumor in image by using feature extraction methods along with CNN.

3.1. Dataset Utilised

The latest 2023 RSNA (Radiological Society for North America) Screening Mammography Breast Cancer Dataset [16] is taken for the research which is publically available at Kaggle website. The data is mainly collected from Australia and the United States**.**

3.2. Convolution Neural Network

Standard Artificial Neural Network (ANN) models consist a single input and output layer and several layers of hidden complexity [11]. Below is a general equation representing the relationship between an individual neuron's vector input X and its vector output Y, expressed in terms of the function F.

$$F(X, W) = Y$$

where W represents vector weight that quantifies degree of coupling among neurons in two neighbouring layers. With resulting vector weight, picture classification tasks may be carried out. There is a sizable body of work discussing the topic of image classification based on pixels. However, additional context such as the image's shape improves performance [12]. The capacity to classify data depending on its context is what has brought a lot of attention to the Convolutional Neural Network model. Figure 1 provides a high-level description of CNN model. Four basic structure blocks are convolution layer, the pooling layer, the activation function and the fully linked layer form the basis of every given CNN model.

3.2.1. Convolution Layer

The input layer takes a target image for classification and the output layer generates a predicted class label based on the image's features [13]. The accessible field is local correlation among neurons that occurs when one neuron in the subsequent layer connects to approximate neurons in the earlier layer [14]. Receptive fields are utilised to extract local features from input image [15]. Every neuron in the following layer has accessible arena that resembles to a particular region in the layer below it and this vector weight is continuous at all plugs on the plane. Because the plane's neurons have same weights, they can identify patterns that appear in the input data despite their dispersed placement [14]. Figure 2 below illustrates this point.

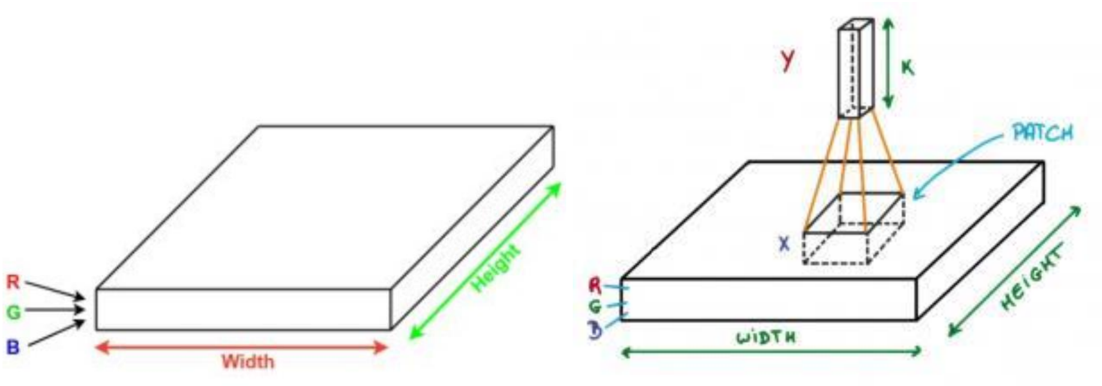

Figure 2: Next Layer Receptive field in Neuron

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To create the feature map, the vector weight (also called a kernel or filter) is slid above the vector input [11]. Convolution operation describes this technique, which involves horizontally and vertically moving the filter. This procedure takes an image input and excerpts N filters and N feature maps, where N derives number of features extracted from image. The quantity of trainable parameters is drastically cut due to the local receptive field phenomenon. Below we see how the convolution process, using the formula given in [12], is used to compute the output aij for position (i,j) in the subsequent layer:

$$a_{ij} = \sigma((W * X)_{ij} + b)$$

When X is the layer's input, W is the kernel or filter that slides over the input, b represents bias, * stands for operation of convolution and represents the non-linearity familiarized to the network.

3.2.2. Pooling Layer

The precise feature location is less important after it is discovered [10]. Therefore, a sub-sampling or pooling layer comes after the layer of convolution. When utilising the technique of pooling number of trainable parameters is drastically reduced and transformation invariance is introduced. As shown in Figure 3, an operation pooling is performed by selecting a window and then passing the input items that fall inside that window through function of pooling.

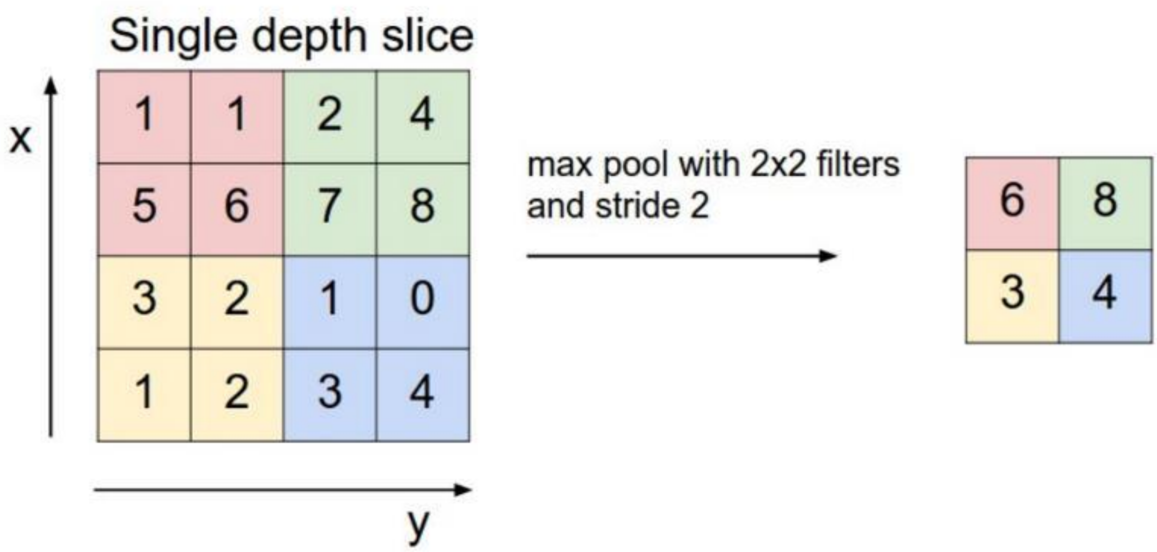

Figure 3: operation of pooling with 2X2 filter

When applied, the pooling function creates a new vector of results. Max-pooling is the most used pooling approach because of its large reduction in map size [11]. Other pooling strategies include average pooling and min-pooling. Meanwhile the winning node ensures not to contribute forward flow, the mistake is not back-propagated to it throughout the computation.

3.2.3. Fully Connected Layer

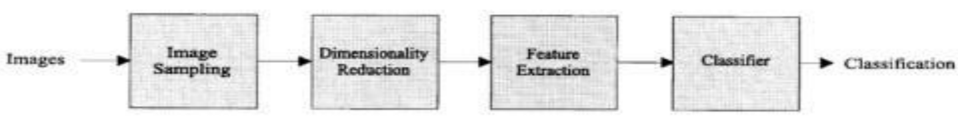

Figure 1. CNN Model

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The entirely linked layer can be compared to the traditional fully connected network. Dot product of vector weight and vector input is designed to get absolute output using the information obtained from the first phase's output (which comprises convolution and pooling repetitively). The cost function is minimised using an offline approach called gradient descent, which estimates cost over the full dataset training and adjusts parameters after every epoch. One epoch is equivalent to walking through the complete dataset. The produces global minimums but if dataset training is huge, it proceeds a very lengthy time to train network. Stochastic gradient descent was implemented in place of cost function reduction method.

3.3. Grad CAM

The knowledge behind Grad-CAM is same as basic CAM (Class Activation Mapping) to use the spatial information saved by convolutional layers for identifying areas of an input image remained relevant for classification judgement. Grad-CAM is used on Neural Network (NN) that has been trained. The NN's weights are stable. To feed an image into network for generate a Grad-CAM heatmap for certain class of interest.

So, Global Average Polling (GAP) is the foundation of CAMs [10], and it has been shown to have exceptional localization skills [15]. In order to do the actual classification, the GAP operation takes the average of the maps of feature from the last layer of convolutional and passes them to final fully connected layer. To create class activation maps, then simply do a weighted sum on each class's maps features from the last layer of convolutional. The precise value of activation map class Mc(x,y) for a given class c and coordinates (x,y) in the input image is:

$$M_C(x,y) = \sum_k \omega_k^c A_K(x,y)$$

where $A_k(x,y)$ is the feature map k activation value at position (x,y) in the latest convolutional layer, and kc is the feature map k and class c weight. Feature maps in the final convolutional layer with a high activation value make logical sense as causes of high CAM values at coordinates (x,y).

3.4. Bounding Box

In image processing projects, the purpose of bounding box is to acts as a reference point for object detection for a particular element. A bounding box is an imaginary rectangle that acts as a point of location for object recognition and builds a collision box for that object. These collision box are drawn over images by data annotators identifying the X, Y item coordinates of interest inside each image.

Object detection is a two-part learning problem: locating and labelling objects. Cutting-edge object detectors as of right now. Image objects can be identified using rectangles called "bounding boxes." Annotations using bounding boxes can take several forms. The coordinates of the bounding boxes are represented in each format in a somewhat different way. The bounding box can be denoted as 4-dimensional vector with coordinates of the box's boundaries: (x_1, y_1, x_2, y_2) R4. In its place using CNN's (x, y, w, h) coordinate system, we employ the parameterizations based on (x1, y1, x2, y2) coordinates [13]:

$$\begin{aligned}
\boldsymbol{t_{x_1}} &= \frac{x_1 - x_{1\alpha}}{\omega_\alpha}, \boldsymbol{t_{x_2}} = \frac{x_2 - x_{2\alpha}}{\omega_\alpha} \\
\boldsymbol{t_{y_1}} &= \frac{y_1 - y_{1\alpha}}{h_\alpha}, \boldsymbol{t_{y_2}} = \frac{y_2 - y_{2\alpha}}{h_\alpha} \\
\boldsymbol{t^*_{x_1}} &= \frac{x^*_1 - x_{1\alpha}}{\omega_\alpha}, \boldsymbol{t^*_{x_2}} = \frac{x^*_2 - x_{2\alpha}}{\omega_\alpha} \\
\boldsymbol{t^*_{y_1}} &= \frac{y^*_1 - y_{1\alpha}}{h_\alpha}, \boldsymbol{t^*_{y_2}} = \frac{y^*_1 - y_{2\alpha}}{\omega_\alpha}
\end{aligned} \tag{1}$$

The expected shifts are denoted by t_{x1}, t_{y1}, t_{x2}, t_{y2} Time constants: $t^*_{x_1}$, $t^*_{y_1}$, $t^*_{x_2}$, $t^*_{y_2}$ The real-world differences are denoted. From the anchor box: $x_{1\alpha}, x_{2\alpha}, y_{1\alpha}, y_{2\alpha}, \omega_\alpha, h_\alpha$ The points . x_1, y_1, x_2, y_2 all fall inside the bounds of what was expected. Since we can optimise each individual bounding box coordinate, we simply refer to them as "x." Obtain a location estimate and a confidence estimate for localization. Instead of just predicting a single location, our network provides a formal probability distribution. The coordinates are free-floating and use a single-variable Gaussian distribution, but other distributions, such as multivariate Gaussian or a blend of Gaussians, are possible.

$$\boldsymbol{P_\theta(X) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x - x_\varepsilon)^2}{2\sigma^2}}} \tag{2}$$

Where Θ is the space of tunable variables. The approximate location of the box is denoted by $\boldsymbol{x_\varepsilon}$. The uncertainty in an estimate can be quantified using the standard deviation. Our network has a high degree of

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confidence in the anticipated bounding box position when σ → 0. The CNN's fully-connected layer sits atop the network to get this effect.

In addition to being expressed as a Dirac delta function, the position of bounding box ground-truth along with Gaussian distribution σ → 0 can be written as

$$P_D(X) = \delta(x - x_g) \qquad (3)$$

Where x_g represents bounding box location using ground-truth.

4. Experimental Analysis

CNN is trained using the 2023 RSNA Screening Mammography Breast Cancer dataset along with Grad-CAM in python platform**.** At first the data pre-processing is done with CNN layers like Convolutional *Layer which is* a usual neural network in every input neuron is linked to the next hidden layer. The dimensionality of feature maps is concentrated using Pooling Layer. Within the CNN's hidden layer, numerous activation and pooling layers will be present. Finally, Fully-Connected layer the connects input layer which is an output from as the final Pooling.

Then for identification of breast cancer tumor, Convolutional Neural Network algorithm along with Grad-CAM is used for extracting features and to filter the images. For this initially gradients weights have to be calculated. So, by using Wandb platform the weights are given for CNN to strengthen the connection between two neurons. The Wandb platform is a machine learning development platform for real time analysis.

Using above weights for identifying selective search of the tumor with function is evaluated with IoU (Intersection over Union) of the ground truth box. For that label foreground is set as 1 and label background is set as 0. Because a basic heuristic is used to decide which intensities are most likely background. The pixels that do not match these are referred to as the foreground pixels. So, the object interest is foreground and remaining are background. Then the image learning is transferred to the learning model for selective search of tumor in image.

The normal image of breast is shown in figure 4.

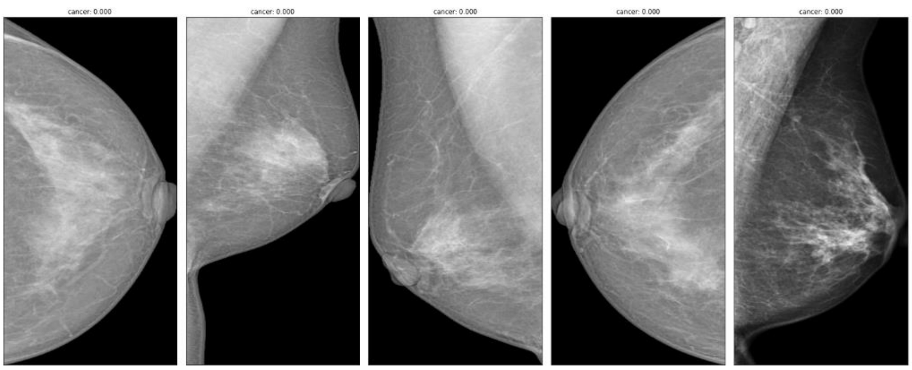

Figure 4: Images Contain Normal Breast images

By observing figure 4, the images have 0% occurrence of tumor so these images are normal and bounding boxes are not formed because there is no abnormality in the mammography images.

Next Grad-CAM model is applied on selective search image; the bounding box is created with a foreground region and threshold confidence (means probability of image being detected correctly) which is identified as a breast cancer tumor as shown in figure 5.

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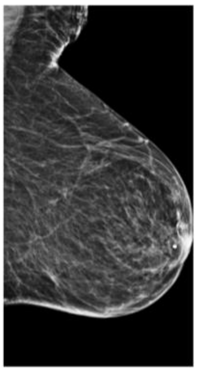
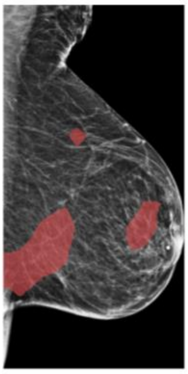
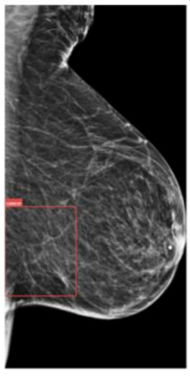
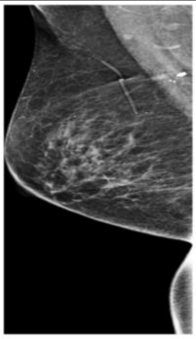
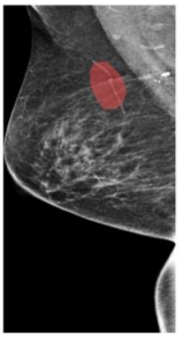
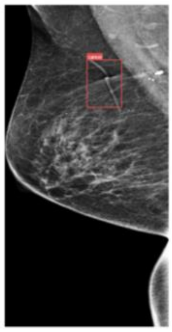
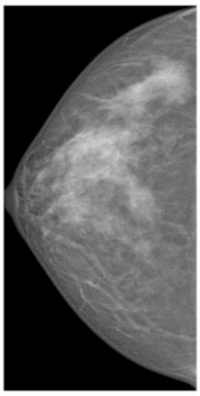
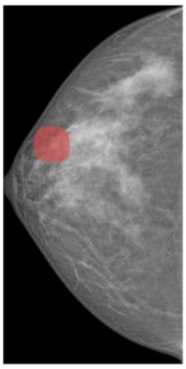
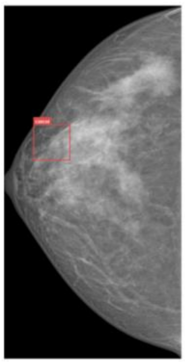
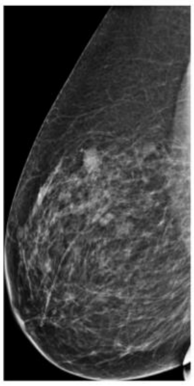
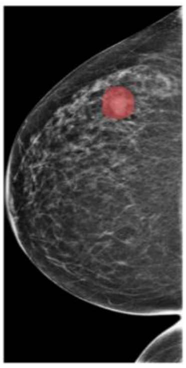
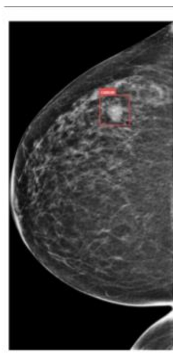
S.No.	INPUT IMAGE	MASK IMAGE	BBOX
a.			
b.			
C.			
d.			

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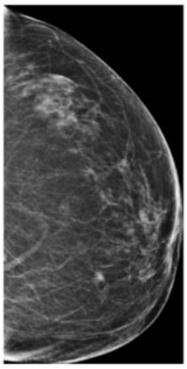
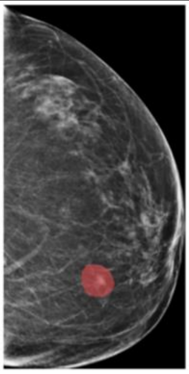
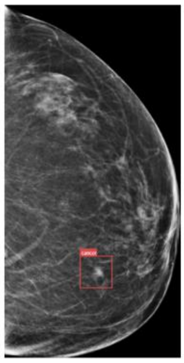
e.			

Figure 5: Tumor Identification with Bounding Box

In the figure 5 (a) to figure 5(e), in masking image the tumor portion is hided for true identifcation of breast cancer tumor. Whereas in Bounding Box image the bounding box is obtained in red color with a rectangle box on image which represents location of breast cancer tumor.

At last test model accuracy of identifying breast cancer tumor which is shown in table 1.

Table 1: Training and Testing CNN Model with Brad-CAM and Bounding Box

Precision	**Recall**	**F1-Score**	**Accuracy**
97%	96%	98%	98.8%

By observing Table 1, CNN with Grad-CAM and Bounding training and testing models has the accuracy of 98.8% of finding or identifying the tumor. whereas precision is 97%, recall is 96%, F1--score is 98%.

The comparison of CNN model and feature extraction technique: Gradient-Weighted Class Activation Mapping (Grad-CAM) and Bounding Box (BB) along with CNN as shown in Table 2.

Table 2: Comparison of Methods

Method	**Precision**	**Recall**	**F1-Score**	**Accuracy**
CNN along with Grad-CAM and BB	97%	96%	**98%**	**98.8%**
CNN	**98%**	**98%**	**98%**	97%

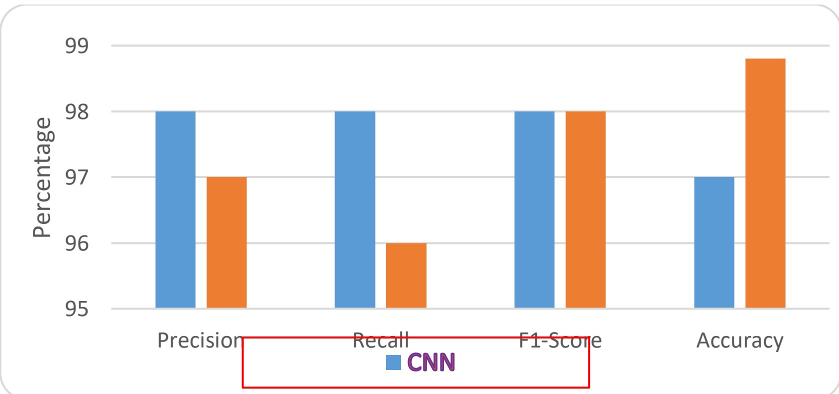


Figure 6: Comparison of Performance Metrics

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By observing table 2 and figure 6, feature extraction technique: CNN with Grad-CAM and BB is best for predicting and locating the breast cancer tumor with 98.8% accuracy.

5. Conclusion

The mortality rate among women from malignancy is high due to breast cancer. To summarise and update the existing information regarding breast cancer, focusing on its current epidemiology, risk factors, categorization, prognostic biomarkers and accessible treatment methods, which resulted in 684,996 deaths at an age-adjusted (population under study) rate of 13.6/100,000. Considering that modifiable risk factors may be crucial in identifying breast cancer incidents, it is urgent to provide the most effective prevention given the dramatic rise in breast cancer morbidity and mortality over the past few eras. Predicted the breast cancer tumor by applying the feature extraction techniques: Grad-CAM and Bounding Box (BB) along with CNN on 2023 RSNA screening Mammography Breast Cancer dataset. Here, for image recognition task and to process the network CNN algorithm. Then after recognising the tumor exact location of tumor has to predicted using Grad-CAM with BB because Grad-CAM will allow to analyse high resolution images effectively in computer vision techniques and BB will locate and identify the object in image. So, CNN with Grad-CAM and BB predicts the exact location of breast tumor in mammography images more accurately with 98.8% high accuracy.

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