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# Breast Cancer Identification using Hybrid Algorithm

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**Abstract:** The Soft Computing has the prospective to predict diseases based on features buried in data. Incidence and humanity rates from breast cancer have risen steadily during the previous three eras. In 2023 it is estimated 3,00,590 people were diagnosed with breast cancer. Around 2,97,790 new cases are diagnosed in women at every month. By 2030, experts predict that the annual number of new cases analysed will have reached 2.7 million with 0.87 million deaths. This breast cancer caused by many factors like various Clinical, Social, Lifestyle and Economic. So key challenge of predicting the breast cancer is the construction of prototype for addressing all notorious risks factors. The feature extraction will improve the predictive performance of a model with Convolutional Neural Network (CNN). This will retain a new recognition task based on existing network with trained weights. In addition, this model will improve the quality of extraction so it makes the best choice for analysis. In this article, hybrid method Convolutional Neural Network (CNN) with Deep feature extraction method i.e., Soft Convolutional Grad-CAM (SCGC) method is proposed to identify the breast cancer tumor along with to know whether cancer is in nodes of lymph or spread to other parts of the body.

***Key words:*** *Breast Cancer, Convolutional Neural Network, Soft Convolution Grad CAM, Feature Extraction.*

## 1. Introduction

Worldwide, women's are being diagnosed by breast cancer are growing and it is the primary cause of mortality between females [1]. Diagnosing breast cancer takes time and requires the expertise of pathologists. The nuclei's morphology, micro- and macrostructure, and other visual characteristics are all taken into account when making a diagnosis by a pathologist. Pathologists' decision-making processes can be streamlined with the aid of CAD technologies. These methods can also lessen differences between observers, leading to more reliable diagnoses. On picture classification and object detection tasks, deep learning systems have achieved performance on equality with human specialists [2]. The utmost common framework deep learning is used for complex discriminative characteristics among image classes is CNN.

In the first study [15] 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 determine key info in both time series and image data. For this purpose, it is extremely valued for image associated 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 it is analysed how finest CNN algorithm is analysed and finding breast cancer with accurateness and also tried to analyse at what age cancer is frequently happened in women.

So, for predicting breast cancer image processing has to be done because it can guide medical interventions such as surgical planning and medication planning etc. Hence, feature extraction is the best method because it can identify the most discriminating characteristics in the image.

The second study [16] is carried out for predicting the breast cancer tumor with a feature extraction process: Grad-CAM (Gradient-Weighted Class Activation Mapping) and Bounding Box (BB) along with CNN. Because the Grad-CAM will visualise and identify the location. Whereas BB acts as a guideline point for object recognition and creates a collision box for that element. At first CNN will obtain region of the annotates objects with in the image then extract feature with Grad CAM and then predicted the tumor with the BB that describes the tumor location. This method gives more accurate results in predicting the tumor and its location. The prediction accuracy of CNN alone and CNN with Grad-CAM and BB is compared. The CNN with Grad-CAM and BB has higher accuracy of prediction.

The method CNN with Grad-CAM and BB is limited to rectangle shape only and it may miss small objects. To overcome this limitation third study has been conducted. For that a deep feature extraction method is smeared to improve the adaptability and scalability of image.

In this article, a hybrid method Convolutional Neural Network (CNN) with Deep feature extraction method i.e., Soft Convolutional Grad-CAM (SCGC)

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method is proposed to identify the breast cancer tumor along with to know whether cancer is in nodes of lymph or spread to other parts of the body.

## 2. Literature Review

Pathologists assign grades to cancers based on what they see on histopathology slides, including microscopic and macroscopic structures. Even though it's monotonous, this work is essential for both treatment and diagnosis. The use of CAD to aid pathologists in making these judgements has come a long way. Typical CAD methods necessitate extraction of features based on nucleus's and its micro-environment's texture and appearance [5, 6, 7]. The nuclei and their surrounding textures can be described in terms of their perimeter, solidity, compactness, smoothness, extent, eccentricity, minor axis length corresponding diameter and foremost axis length. Histopathology entities, like nuclei or patches, have their classification determined using these attributes and analytical techniques including fuzzy-Cmeans, Gaussian mixture models, MLP, SVM and clustering algorithms. Once widely used, these techniques no longer generalise well to huge datasets. In situations when there is a mountain of data, deep learning models excel. These approaches are able to learn complex features from histopathology slides and are resistant against human-induced errors in slide preparation as well as between patients, disease situations, and hospitals. The use of CNNs is common in deep learning-based methods [8, 9]. While deep learning techniques are extensively researched for use in categorization of histopathology images, little research has been conducted on the visualisation or localization of histopathology datasets. Good visualisation on natural images can be achieved based on gradient methods like Deconvolution [10], Backpropagation [10] and Grad-CAM [11], but these methods fall short when applied to histopathology images due to the difficulties presented by their huge size, variation through disease conditions and human generated errors in slither training. For the sake of classification and localization, he employed attention based multiple learning instance technique to histopathology images.

## 3. Methodology

This paper main aim is to identify the breast cancer tumor is in nodes of lymph or spread to other parts of the body by proposing a Hybrid Soft Computing method. Because hybrid feature extraction will have combined features from first and second methods for predicting the object with more prediction accuracy, generalization and robustness. Here, the hybrid algorithm is generated using Convolutional Neural Network (CNN) with Deep feature extraction method i.e., Soft Convolutional Grad-CAM (SCGC) method.

### 3.1. Dataset

The up-to-date dataset 2023 Radiological Society for North America (RSNA) Screening Mammography Breast Cancer Dataset [14] is considered for the research which is taken from Kaggle web site. The breast cancer screening programmes are mainly collected from Australia and the United States.

### 3.2. Convolutional Neural Networks (CNN)

CNN can be used to explore the patterns in images. And it can be done with the convolution of the images [4]. At the early stages of CNN, the straight lines and sharp angles can be identified by the network. With the application of Neural Networks, the subtler details can be picked out as delve deep with the pattern in images and it is because of this characteristic that makes CNN effective at object detection [3]. The proposed technique is employed with CNN for the identification of breast cancer over the photographic evidence.

The visualised Figure 1 describes that the CNN architecture has three distinct layers: pooling layer, convolutional layer, fully connected layer. The output of the Neurons connected to the nearby areas is computed in the first layer and for determining each of them, a dot products of weight and the area is used. The filters used as input to the images have the usual size of 3,5or8 square pixels. Initially, the recurring patterns appearing all over the image are learnt by the filters and then the filters learn from the entire image by examining them using sliding window protocol.

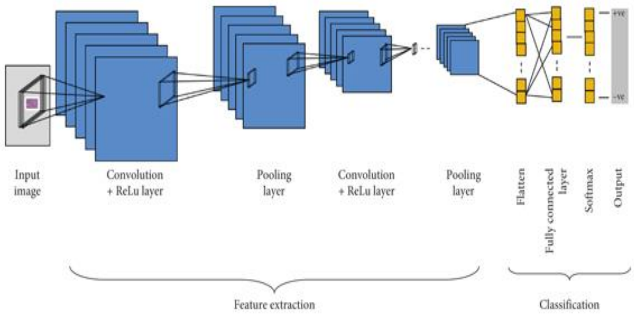



**Fig 1:** Typical Architecture of CNN (Google Courtesy)

### 3.3. Soft Convolution Grad CAM

The Soft Convolution Grad-CAM (SCGC) is a generalised gradient based visual explanation for deep feature extraction that makes model interpretable and transparent. This model will work with the grad-cam model and convolutional networks to predict the visual explanations for neural network on image data.

Localization map coarse emphasising the significant regions in image for forecasting the thought is generated by Grad-CAM (Gradient-weighted Class Activation Mapping) [12] which usages gradients of target thought (ex: 'dog' in classification sequence or network of words in captioning network) elegant into the final layer of convolutional [13].

In addition, the information of spatial is normally layers with fully-connected is lost naturally retained in convolutional layers, thus anticipate the final layers of convolutional to represent optimum balance among high-level semantics and precise information's of spatial. Layers of neurons in layers scan a picture for evidence of an exact semantic class (such as an object's pieces). Grad-CAM gives each neuron a weight based on the input streaming into final layer of convolutional will help to make judgement. Although our method can have used to describe initiations in layer of a deep network, our current slog focuses solely on clarifying decisions made the output layer.

$$L^C_{Grad-CAM} \in \mathbb{R}^{uXv}$$

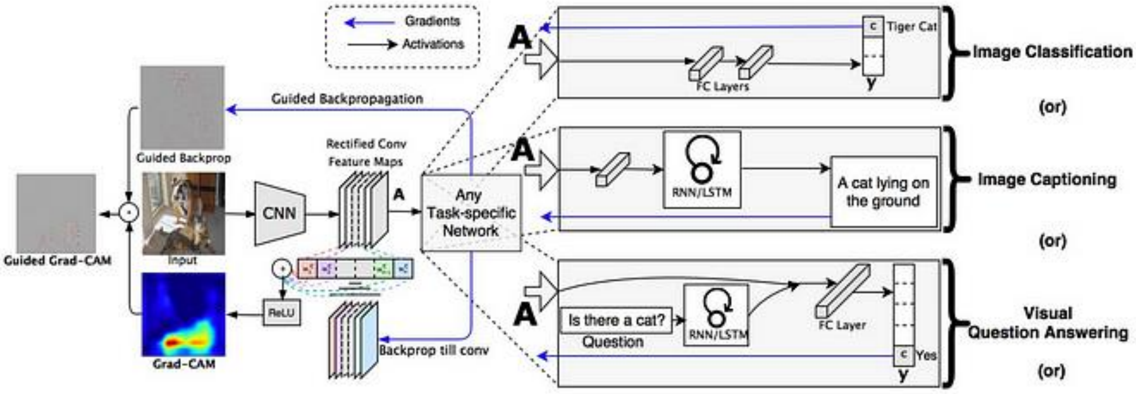



**Figure 2:** Soft Convolutional Grad-CAM overview [11]

Grad-CAM is used to generate a discriminative localization map for different classes, as shown in Figure 2. To train a Grad-CAM model, first calculate score gradient for class c, $y^c$ (earlier the softmax), through regard initiations of a layer's in convolutional for feature map, that is $y^c$ $A^k$. The significance weights c k for each neuron are calculated by taking a global average of the gradients that are flowing back along the $i^{th}$ and $j^{th}$ dimensions.

$$\alpha^c_k = \frac{1}{z} \sum_i \sum_j \frac{\partial y^c}{\partial A^k_{ij}} \qquad (1)$$

The precise computation of $\alpha^c_k$ during gradient back propagation with details to activations quantities to the product of weight matrices and gradient with details of function activation at each layer of convolution. This weight $\alpha^c_k$ seizures the 'importance' of k feature map for c target class and hence denotes a partial linearization of deep network downstream from A. $\frac{\partial y^c}{\partial A^k_{ij}}$ represents gradients via backprop, $\frac{1}{z} \sum_i \sum_j$ represents global average pooling.

Finally, a ReLU was used after a weighted blend of maps of forward activation to produce,

$$L^c_{Grad-CAM} = ReLU(\textstyle\sum_k \alpha^c_k A^K) \qquad (2)$$

Here $(\sum_k \alpha^c_k A^K)$ represents linear combination To find the characteristics that positively affect the class of interest (the pixels whose intensity would be improved to increase $y^c$), a ReLU is used to the linear mixture of maps. The class score generated by a CNN for image classification is not need to be $y^c$.

## 4. Experimental Analysis

CNN is trained with the 2023 RSNA Screening Mammography Breast Cancer dataset along with soft convolutional Grad-CAM in python platform. Then the offset correction is done for images by removing sever shadow because the object in the image become more clear which is visualised in figure 3.

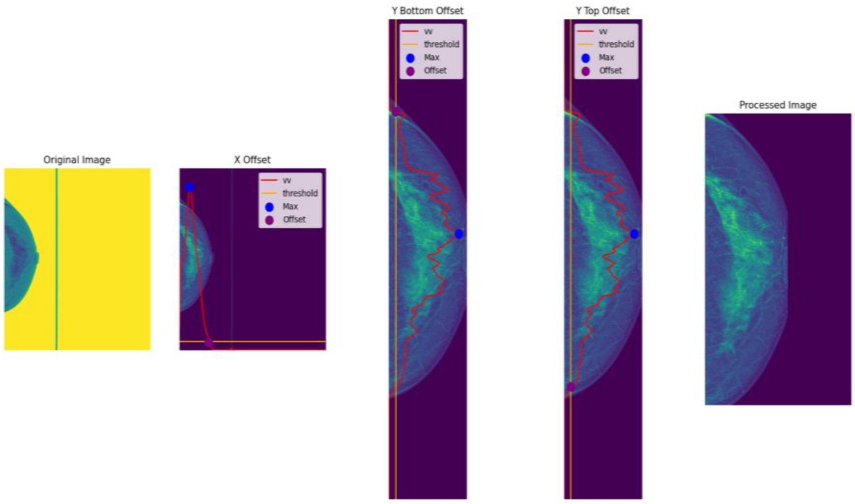



**Fig 3:** Offset Image

In figure 3, the input images are cropped with x-offset, Y bottom and top offset is done with threshold and widths for processed image will crop the edges and object can be clearly visible, to increase the image brighter and contrast for prediction

Then for identification of breast cancer tumor convolutional neural network algorithm along with soft convolution Grad-CAM is used. Because it computes and locate multiple occurrence in object accurately. For this initially gradients weights and biases are needed. So, by using Wandb platform the weights and biases are given for the CNN to strengthen the connection between two neurons. The Wandb platform is a machine learning development platform for real time analysis. So that the initialised model was built to reduce the image with high dimensionally without losing its information. The initialized model is visualized in figure 4 with gradients of cost on x-axis and frequency of occurrence while computing on y-axis with states that the model is operating and controlling the system with a great performance and processing time for predicating the tumor accurately.

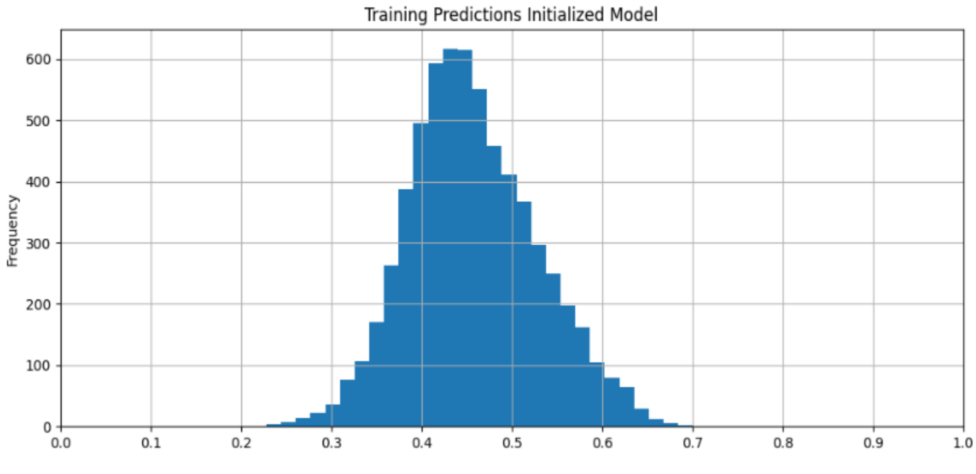



**Fig 4:** Visualizing the Performance of Initializing Model

The initialized CNN model is applied on data to evaluate with epoch using Learning Rate Schedule callback because it will allow us to identify a function that call each epoch in order to modify learning rate. The learning rate epochs has various types because it shows the training neural network that can used for gradient calculation to make learning rate adaptive to the gradient descent optimization procedure to identify the tumor in breast. The step learning rate epoches are presented in figures 5(a) to 5(e).

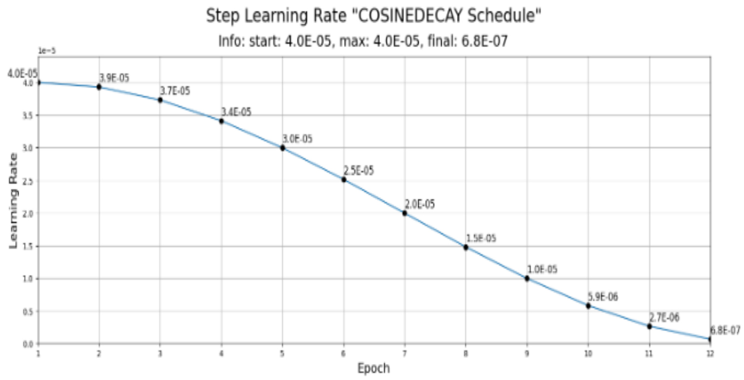



**Fig 5** (a): Epochs learning rate cosinedecay schedule

By observing figure 5 (a) cosinedecay schedule, will schedule the epochs based on learning rate here the epochs are started with large learning rate then it rapidly decreased to minimum value for easy restart of the algorithm.

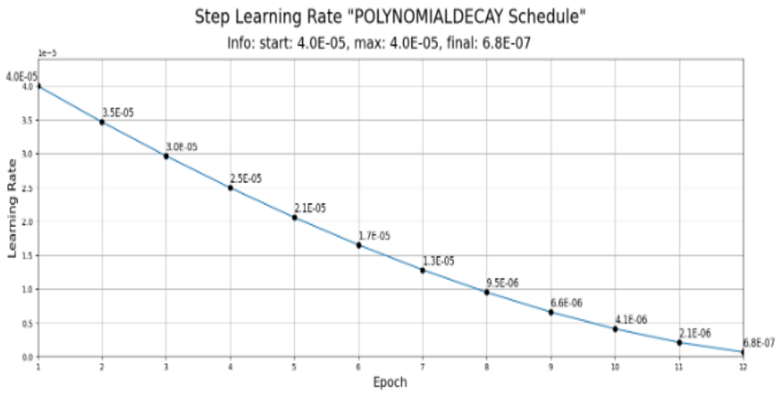



**Fig 5** (b): Epochs learning rate Polynomialdecay schedule

By observing figure 5 (b) Polynomialdecay schedule decreases the learning rate as a epoch function number to maximize the easy function of algorithm.

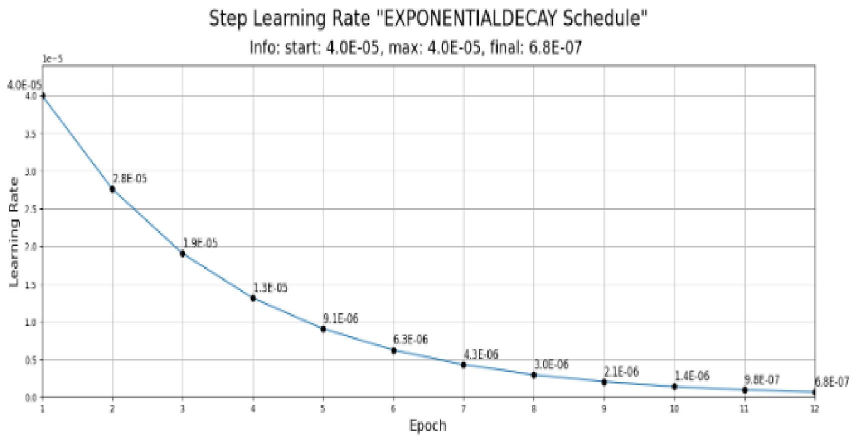



**Fig 5** (c): Epochs learning rate exponentialdecay schedule

By observing figure 5 (c), the schedule of exponential decay function is used to optimize step for initial learning rate which shows the iterations of epochs.

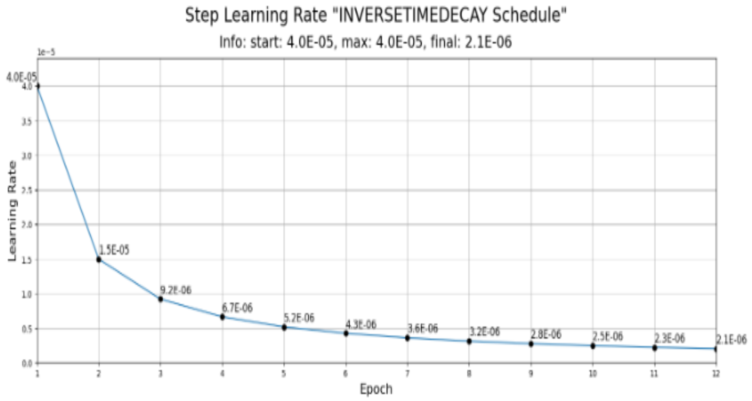



**Fig 5** (d): Epochs learning rate inversetimedecay schedule

By observing figure 5 (d) inversetimedecay schedule is an optimizer step that gives an initial rate with updated weights of gradients in the network.

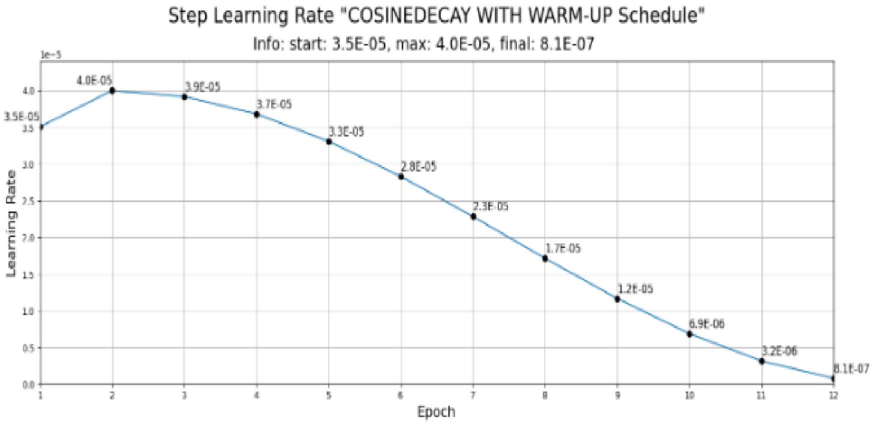
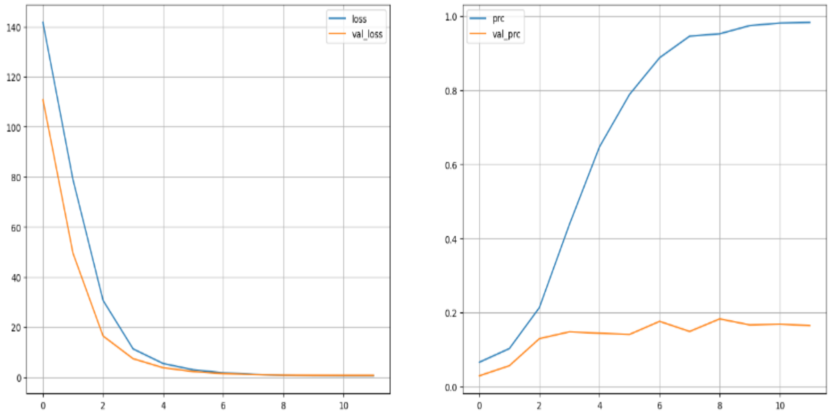



**Fig 5 (e)**: Epochs learning rate consinedecay with warm-up schedule

By observing figure 5 (e) consinedecay with warm-up schedule which increases the learning rate from 0 to stipulated value by certain epochs in time. Also, it shows that the linear rate starts at high point and reached to its max point which means that the learning CNN algorithm is best fit for gradient application for identifying tumor in breast cancer.

In this work when CNN model is applied "How good it performs is evaluated" by observing loss and process function of the model is visualized in figure 6 (a) and in figure 6(b).




(a) (b)

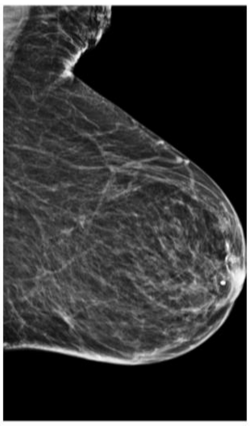
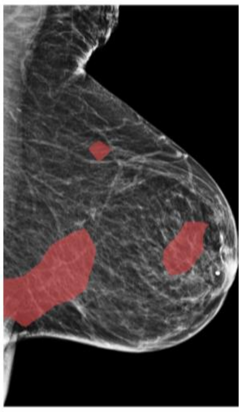
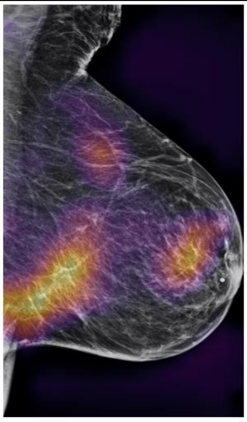
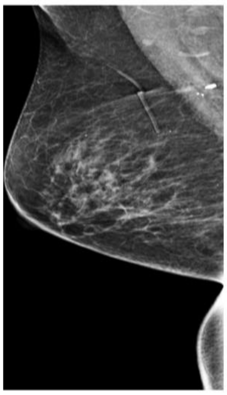
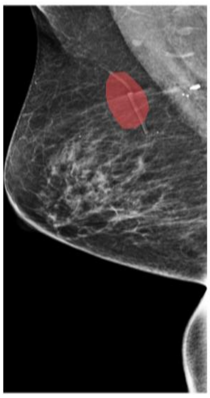
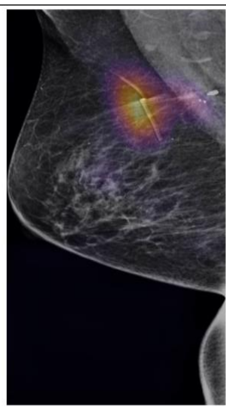
**Fig 6:** Loss and Progress of the CNN Model

In figure 6 (a) X-axis is loss and Y-axis is error rates. Here it is observed that the loss is less and the value of loss errors are also less so the performance of the model is good. Whereas figure 6 (b) X-axis is process and Y-axis is count. Here it is observed that the process and value performance is increased gradually so performance of model is optimized.

Now the proposed hybrid algorithm Deep feature extraction technique i.e., soft convolutional Grad CAM is applied with the trained network to identify the parts of the tumor. It also identifies the exact place of tumor more accurately to know whether cancer is in nodes of lymph or spread to other portions of body. The predicted breast cancer tumor is visualised in the figure 7 and figure 8.


**Fig 7:** No Tumor images

By observing figure 7, the images have 0% occurrence of tumor so these images are normal because tumor is not identified in the mammography images.

| S.No. | INPUT IMAGE | MASK IMAGE | GRADCAM IMAGE |
|---|---|---|---|
| **a.** |  |  |  |
| **b.** |  |  |  |

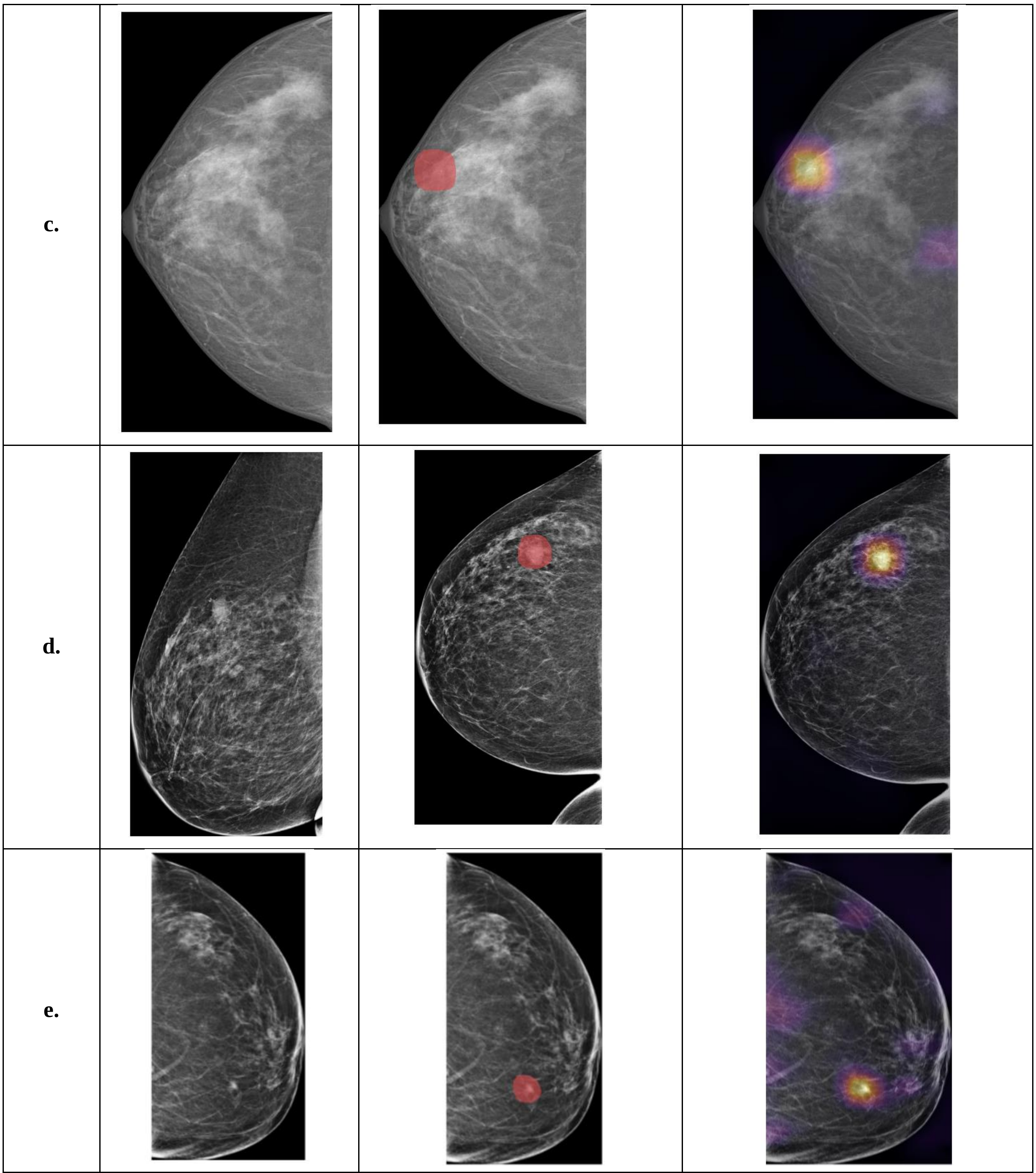



**Fig 8:** Abnormal images

By observing figure 8 (a), i.e., masking images and Grad CAM images, tumor is idenfied and by observing Grad CAM image the yellow part is the tumor and voilet part is spreading part so the patient having many tumors in breast.

By observing figure 8 (b), i.e., masking images and Grad CAM images, tumor is idenfied and by observing Grad CAM image the yellow part is the tumor and voilet part is spreading part so the patient having moderate tumor in breast.

By observing figure 8 (c), i.e., masking images and Grad CAM images, tumor is idenfied and by observing Grad CAM image the yellow part is the tumor and voilet part is spreading part so the patient having moderate tumor in breast.

By observing figure 8 (d), i.e., masking images and Grad CAM images, tumor is idenfied and by observing Grad CAM image the yellow part is the tumor and voilet part is spreading part so the patient having normal tumor in breast.

By observing figure 8 (e), i.e., masking images and Grad CAM images, tumor is idenfied and by observing Grad CAM image the yellow part is the tumor and voilet part is spreading part so the patient having severe tumor and it spreaded in breast.

Finally, performance of the proposed model in terms of accuracy, recall, precision and F1-Score for predicting breast cancer tumor is in nodes OF lymph or spread to other parts of body is presented in table 1.

**Table 1.** Performance of Model Accuracy

| Precision | Recall | F1-Score | Accuracy |
|---|---|---|---|
| 99% | 98% | 99% | 99.1% |

As per table 1, CNN Model with Soft Convolution Grad CAM model has the accuracy of 99.1%, whereas precision is 99%, recall is 98% and F1-score is 99%.

The comparison of proposed hybrid method CNN with Deep feature extraction method i.e., Soft Convolutional Grad-CAM (SCGC) with my previous works methods like feature extraction technique: Grad-CAM (Gradient-Weighted Class Activation Mapping) and Bounding Box (BB) along with CNN and CNN model [15,16] as presented in table 2 and visualised in figure 9.

**Table 2:** Comparison of Algorithms

| Method | Precision | Recall | F1-Score | Accuracy |
|---|---|---|---|---|
| **CNN with SCGC** | **99%** | **98%** | **99%** | **99.1%** |
| **CNN along with Grad-CAM & BB** | 97% | 96% | 98% | 98.8% |
| **CNN** | 98% | 98% | 98% | 97% |

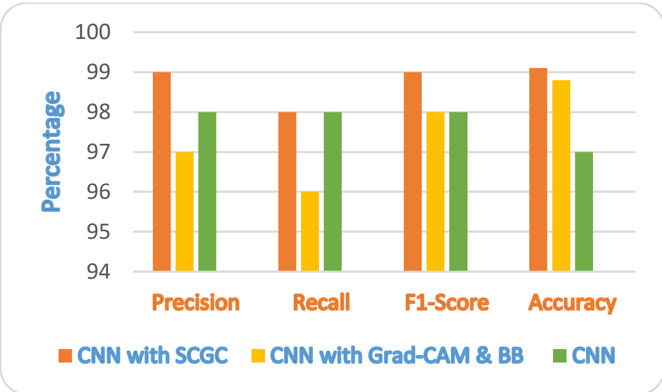



**Fig 9:** Comparison of Performance Metrics

By observing table 2 and figure 9, deep feature extraction technique: CNN with SCGC is finest method for predicting the breast cancer tumor with highest accuracy of 99.1%.

## 5. Conclusion

For image prediction feature extraction technique is the best method along with CNN which is popular algorithm because it analyse the basic shape to learn features of the image deeply for more accurate prediction. So to determine or predicting the breast cancer is in lymph node or spread to other parts of body will state the stage of cancer is a helpful guide for treatment. So, to identify the breast cancer tumor a hybrid method Convolutional Neural Network (CNN) with Deep feature extraction method i.e., Soft Convolutional Grad-CAM (SCGC) method is proposed. The breast cancer tumor is identified whether cancer is in nodes of lymph or spread to other portions of body with model accuracy 99.1%. Finally compared with the previous works like CNN, Grad-CAM & BB along with CNN and CNN with Soft Convolutional Grad-CAM (SCGC). The CNN with Soft Convolutional Grad-CAM (SCGC) is the finest algorithm for breast cancer prediction with 99.1% accuracy.

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