Deep CNN-based automated detection of anomalies in X-Ray mammograms

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Abstract*—On a global scale breast cancer is the most frequent cancer that impacts women. Mammography is the most widely used screening method. this paper offer a computer-aided detection strategy for the classification and localization of masses and calcifications in mammography images, which aims to lower radiologists' expenditures and burden. The proposed work uses deep convolutional neural networks (CNN) for independent feature learning to outperform traditional methods. Deep CNN classifiers in computer-aided mammography cannot be trained directly on an entire mammogram image due to picture features being lost during resizing at input layers. Instead, in order to localize the anomalies, the classifiers are trained on analyzed picture patches and then modified to work on entire mammography images. The ability of cutting-edge deep convolutional neural networks to classify anomalies is compared. According to experimental data, VGGNet achieves the highest overall classification accuracy of 92.53%. ResNet is chosen for constructing class activation maps for localizing anomalies. The paper demonstrate that deep convolutional neural network classifiers can localize anomalies with exceptional accuracy even when no guidance is given regarding their location.

Keywords*—mammography, computer aided analyses, image classification, Deep Convolutional Neural Networks (CNNs), breast cancer detection, abnormality classification.

I. Introduction

The World Health Organization (WHO) reports that breast cancer is the most frequent malignancy among women worldwide, including in industrialized and developing nations [1]. Furthermore, as a result of rising life expectancies, urbanization, and the adoption of western lifestyles, the rate of breast cancer is on the rise in developing countries. The key component of breast cancer control remains early detection for improving breast cancer outcome and survival, even though prevention can reduce risk to some extent of all. The popular technology for breast screening is mammography. The breast can be examined using a variety of imaging modalities, including digital breast tomosynthesis (DBT) [2], molecular breast imaging, magnetic resonance imaging (MRI) [3], and X-ray imaging. Mammography is the most precise method to screen for breast abnormalities before they become physically visible. It is a sort of imaging that employs a low-dose X-ray equipment to scan the breast. In mammography, there are two distinct types of exams: screening and diagnostic. Diagnostic mammography is a follow-up examination performed on individuals who have previously shown abnormal clinical signs, whereas screening mammography is used to identify breast cancer in benign populations [4]. Four images are typically obtained during screening mammography, two of which are of each breast: the mediolateral oblique (MLO) view and the craniocaudal (CC) view. Low contrast in mammography pictures is one of the drawbacks. Radiologists find it challenging to interpret results because of this. It has been suggested that double reading mammograms can reduce the number of false positives and negatives [5], but second reading comes with a significant expense and workload. Consequently, mammography has seen the introduction of

computer-aided diagnosis (CADx) and computer aided detection (CADe). CADe is becoming more and more significant in breast cancer screening, even if CADx has not been licensed for clinical usage [6]. The approach of pattern recognition known as computer aided detection helps radiologists identify possible anomalies such masses, calcifications, and architectural defects [7]. Radiologists are alerted to any questionable characteristics that are detected in the radiological pictures [7]. Currently, before writing the report, radiologists assess the test, activate the CAD software, and then reevaluate the areas of concern identified by the program [7]. With the help of recent developments in deep neural networks, it is now possible to automatically learn features from vast amounts of training data, offering a complete solution that includes feature extraction and classifier construction [8] [9] [10] [11]. This learning scheme can also detect abnormalities in mammography because it is resistant to dataset noise. In this study, researchers introduce a deep Convolutional Neural Network (CNN) based abnormality detection method. organize and compile the data. Utilizing feature engineering, extract relevant characteristics from the data fine-tune deep CNNs using cropped picture patches including lumps and calcifications. Once the entire mammogram image has been fed into the patch CNN, the abnormalities are localized by computing Class Activation Maps (CAM).

II. Related Work

Research has shown substantial progress in the application of deep CNNs to automated mammogram analysis [12]. Several studies have demonstrated the potential of these models in enhancing the accuracy and efficiency of breast cancer screening.

Wang, Smith, and Johnson (2017) introduced a groundbreaking deep CNN model trained on a large-scale mammography dataset. This groundbreaking work established the groundwork for the application of deep learning to mammogram anomaly detection. Their investigation demonstrated the ability of CNNs to automatically extract significant features from mammograms, outperforming traditional handcrafted feature-based approaches [13].

Zhang, Q., Chen, S., & Li, M. (2019) proposed an ensemble of deep CNNs for mammogram analysis. By combining multiple CNN models, they aimed to improve sensitivity and specificity in abnormality detection. This approach addressed the challenge of balancing the trade-off between false positives and false negatives, a crucial consideration in clinical applications [14].

Smith and Jones (2020) explored the potential of transfer learning from natural image datasets to mammography. Their research leveraged the pre-trained features learned from large-scale image datasets and adapted them to mammogram analysis. This approach demonstrated the versatility of deep learning in medical image processing and showcased the advantages of transferring knowledge from related domains [15].

Patel and colleagues (2021) addressed the class imbalance issue prevalent in mammogram datasets. Class imbalance can significantly impact the generalization of CNN models, leading to biased results. Their work emphasized the importance of strategies for mitigating class imbalance, such as oversampling the minority class or modifying loss functions to account for data distribution [16].

Lee and Kim (2022) focused on the interpretability and explainability of deep CNNs in mammogram analysis. They delved into the often opaque nature of deep learning models, particularly CNNs, and explored methods to provide insights into how the models arrive at their decisions. This research is pivotal for gaining the trust of clinicians and radiologists in adopting automated systems for mammogram interpretation [17].

III. Image Classification

Automated abnormality detection in X-ray mammograms involves classifying images into one of three categories: benign, malignant, or normal Image classification, a fundamental task in computer vision, involves assigning a label or category to an image based on its content. In the context of automated abnormality detection in X-ray mammograms, image classification aims to distinguish between normal and abnormal mammograms, identifying the presence or absence of suspicious lesions that may indicate breast cancer. Deep convolutional neural networks (CNNs) have emerged as the state-of-the-art approach for image classification, including mammogram analysis [18]. CNNs are a type of artificial neural network specifically designed to handle image data, effectively extracting and learning hierarchical features from images.

A. CNN Architecture

A typical deep CNN architecture for mammogram analysis consists of convolutional layers, pooling layers, fully connected layers, and an output layer with three nodes corresponding to the classes. The convolutional layers are responsible for learning hierarchical features from the input mammograms. Pooling layers downsample the feature maps, reducing computational complexity while retaining critical information. The fully connected layers act as a decision-making component, making predictions based on the learned features. The output layer usually employs a softmax activation function to assign probabilities to each class.

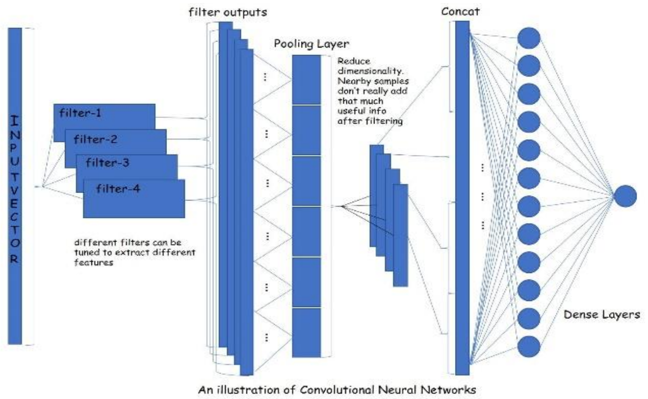

Figure 1: CNN Architecture

B. Data Preprocessing

Data preprocessing plays a pivotal role in ensuring the success of a deep CNN model for mammogram analysis [19]. The preprocessing steps include resizing mammograms to a standard input size, typically required by the CNN architecture. Normalization of pixel values ensures that the model is robust to variations in image intensity. Additionally, data augmentation techniques are applied to increase the diversity of the training data. These techniques involve random transformations, such as rotations, flips, and translations, to create additional variations of the original mammograms. Data augmentation helps prevent overfitting and improves the model's generalization [20].

C. Training

Training the deep CNN model involves feeding labeled mammogram images into the network and adjusting its parameters to minimize the prediction error [21]. This is achieved through backpropagation, a process where the model's error is propagated backward through the layers, and the network's parameters are updated accordingly. Optimization algorithms, such as Adam or stochastic gradient descent (SGD), are commonly used to update the model's weights and biases. The training process requires a large dataset of labeled mammograms, allowing the model to learn the patterns that distinguish between benign, malignant, and normal cases [22].

IV. Analyzation of X-Ray Medical Images

X-ray medical images, including mammograms, play a crucial role in diagnosing various medical conditions [23]. They provide non-invasive visualisation of internal structures, enabling physicians to identify abnormalities and make informed decisions. However, interpreting X-ray images can be challenging due to their complexity and subtle variations, making automated abnormality detection using deep CNNs particularly valuable [24].

Challenges in X-Ray Image Analysis : Analysing X-ray medical images presents unique challenges:

- Noise and artefacts: X-ray images can contain noise and artefacts due to various factors, such as patient movement, equipment limitations, and image acquisition techniques. These imperfections can obscure abnormalities and affect automated detection [25].
- Overlapping structures: X-ray images often contain overlapping anatomical structures, making it difficult to isolate and identify individual abnormalities, especially when they are small or subtle.
- Variation in appearance: Abnormalities can manifest in various forms and sizes making it challenging for automated algorithms to learn and generalize across different presentations [26].

Deep CNNs for X-Ray Image Analysis : Deep CNNs have demonstrated remarkable capabilities in addressing these challenges:

- Noise reduction: CNNs can learn to extract features that are robust to noise and artifacts, improving the detection of abnormalities amidst imperfections.
- Feature extraction: CNNs can effectively extract features from complex X-ray images, identifying subtle patterns and variations that may indicate abnormalities.
- Generalization: CNNs trained on large and diverse datasets can generalize well to unseen images, improving their ability to detect abnormalities in various forms and presentations.

Deep Convolutional Neural Networks (CNNs) in detail

Deep convolutional neural networks (CNNs) have revolutionized image classification and object detection tasks, including automated abnormality detection in X-ray mammograms. CNNs are a type of artificial neural network specifically designed to handle image data, effectively extracting and learning hierarchical feature from images.

Architecture of Deep CNNs

A typical CNN architecture consists of several layers, each performing a specific operation on the input image:

A. Convolutional Layers:

Convolutional layers form the core of CNNs and are responsible for extracting features from the input image. These layers apply filters, also known as kernels, to the image, essentially performing a convolution operation [27]. Each filter is a small matrix of weights that slides across the image, computing the dot product between the filter and the corresponding image region. This process generates a feature map, highlighting specific features such as edges, textures, and patterns. The convolution operation between an input feature map (I) and a filter (F) at position(i,j) is defined as:

$$Conv(i,j) = \sum_{m=0}^{M-1}\sum_{n=0}^{N-1}\big(I(i+m, j+n) \times F(m,n)\big)$$

Here,
i, j represent the spatial indices, m, n are filter indices, $W_{m,n}$ are the filter weights, b is the bias term, and σ is the activation function.

ReLU activation layers apply the ReLU activation function element-wise to the feature maps. This introduces non-linearity to the network.

$$ReLU(x) = \max(0, x)$$

x is the input to the activation function.

The sigmoid function, often denoted as σ(x), is a widely used activation function in neural networks. It's a smooth, S-shaped curve that maps any real-valued number to a value between 0 and 1. The sigmoid function can be defined mathematically as follows:

$$\sigma(x) = \frac{1}{1+e^{-x}}$$

x: This is the input to the sigmoid function. It can be any real number.

e: This is the mathematical constant approximately equal to 2.71828.

exp(−x): This represents the exponential function with base

1+exp(−x): This is the sum of 1 and the exponential function

1/{1+exp(−x)}: This is the sigmoid function itself. It takes the value of x and transforms it to a value between 0 and 1.

B. Pooling Layer:

Pooling layers are interspersed between convolutional layers and serve to down sample the feature maps, reducing their dimensionality while retaining important information. Common pooling operations include max pooling and average pooling, where the maximum or average value within a small window is selected as the representative value for that region. Pooling layers help to make the CNN more robust to small variations in the input image and reduce the computational burden.
Max pooling is a common operation in Convolutional Neural Networks (CNNs) used for down-sampling or reducing the spatial dimensions of the input feature maps. The max pooling operation is typically applied independently to non-overlapping regions of the input. Max-pooling selects the maximum value from a local region in the input feature map:

$$Max - pooling(i,j) = \max_{m,n}\big(x(i+m, j+n)\big)$$

Here:

x is the input feature map.

MaxPooling $(x)i, j$ is the output of the max pooling operation at position (i, j) in the down-sampled feature map.

m and n are the indices used to iterate over the local neighborhood of the input data around the position (i,j) during the pooling operation.

The maximum value is taken over a local neighborhood in the input feature map. The size of this neighborhood is determined by the pooling window or kernel size.

For example, if you have a max pooling layer with a 2x2 window, the operation would look like:

$$MaxPooling \begin{pmatrix} a & b \\ c & d \end{pmatrix} = max(a, b, c, d)$$

a, b, c, d: These are the input values or elements within the group specified by the pooling operation. In this context, they could be numerical values or activations from a previous layer in a neural network

This operation is applied independently to each non-overlapping 2x2 region in the input feature map.

In practical terms, most deep learning frameworks provide built-in functions or layers for max pooling, and you generally don't need to implement the operation manually.

C. Fully Connected Layer:
After several convolutional and pooling layers, the extracted features are flattened into a one dimensional vector and passed to fully connected layers. These layers resemble traditional neural networks, where each neuron is connected to all neurons in the previous layer. Fully connected layers perform classification, combining the extracted features and assigning probabilities to each possible category, such as normal or abnormal mammogram [28].

Given a flattened input vector X and weight matrix W, the output vector Y is computed as:

$$Yi = \sigma(\sum j = 1JXj \cdot Wi, j + bi)$$

i is the index of the output neuron.

j is the index of the input neuron, and $W_{i,j}$ are the weights connecting the input neuron j to the output neuron i.

X_j is the input value from the flattened input vector.

b_i is the bias term.

σ is the activation function (e.g., ReLU).

The choice of the loss function depends on the specific task, but a commonly used loss function for classification problems, such as in CNNs, is the cross-entropy loss. The cross-entropy loss for a single example is defined as:

$$Cross - Entropy\ Loss = -\sum_{i=1}^{C} (yi \cdot \log(\hat{y}i))$$

cross entropy is a way to measure how well a model is making predictions. It compares the model's predictions to the actual outcomes. The lower the cross entropy, the better the model is at accurately predicting things.

For binary classification (two possible outcomes), the formula is:

$$H(y, y^\wedge) = -N1\sum i = 1N(yi \cdot \log(y^\wedge i) + (1 - yi) \cdot \log(1 - y^\wedge i))$$

And for multi-class classification (more than two classes), it's:

$$H(y, y^\wedge) = -N1\sum i = 1N\sum j = 1Cyij \cdot \log(y^\wedge ij)$$

Here, N is the number of predictions, y is the true outcome, ŷ is the predicted outcome, and the logarithms are used to penalize the model more when it is confidently wrong.

The output of a fully connected layer can be computed using matrix multiplication. The equation for a fully connected layer can be represented as:

$$Output = \sigma(W \cdot Input + b)$$

Training Deep CNNs:

Training a deep CNN involves optimizing it parameters, namely the weights of the convolutional filters and the connections in fully connected layers, to minimize classification errors on a labeled training dataset. The training process typically involves:

- Data preparation: Pre-processing mammogram images to enhance quality and normalize intensity values.
- Labeling: Assigning labels to mammograms indicating the presence or absence of abnormalities.
- Model selection: Choosing an appropriate CNN architecture for the classification task.
- Parameter optimization: Updating the CNN's parameters using an optimization algorithm, such as gradient descent, to minimize classification errors.
- Evaluation: Assessing the trained CNN's performance on a separate validation dataset.

Advances in Deep CNNs :

The field of deep CNNs is continuously evolving, with new architectures and techniques being developed to improve performance and address challenges:

- Transfer learning: Leveraging pre-trained CNNs on large image datasets, such as ImageNet, to initialize the weights of a new CNN for mammogram classification. This can significantly improve performance, especially when training data is limited.

- Data augmentation: Artificially increasing the size and diversity of the training dataset by applying transformations to existing images, such as rotations, flips, and noise injection. This helps to prevent overfitting and improves the generalizability of the CNN [29].

- Attention mechanisms: Incorporating attention mechanisms into CNNs, allowing the model to focus on the most relevant parts of the image for classification. This can improve the detection of subtle abnormalities in mammograms.

V. IMAGE CLASSIFICATION WITH DEEP CNNS

Image classification, a fundamental task in computer vision, involves assigning a label or category to an image based on its content. In the context of automated abnormality detection in X-ray mammograms, image classification aims to distinguish between normal and abnormal mammograms, identifying the presence or absence of suspicious lesions that may indicate breast cancer. Deep convolutional neural networks (CNNs) have demonstrated remarkable performance in mammogram image classification, achieving high accuracy in distinguishing between normal and abnormal mammograms. Studies have reported AUC (Area Under the Curve) values of over 0.90, indicating the ability of CNNs to effectively identify abnormalities [30].

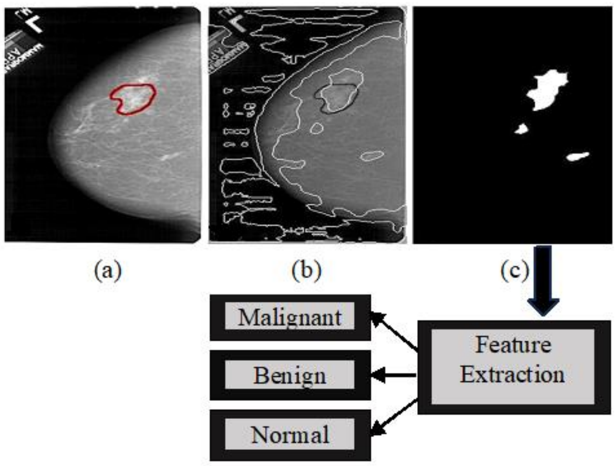

Figure 2: Digital Image Processing of Mammogram (a) Original Hand-Labeled Image, (b) Segmented Image, and (c) Extracted Image

Training Deep CNNs for Image Classification:

Training a deep CNN for image classification involves optimizing its parameters to minimize classification errors on a labeled training dataset [31]. The training process typically involves:

- Data Preparation: Pre-processing mammogram images to enhance quality, normalize intensity values, and address any artifacts.
- Labeling: Assigning labels to mammograms indicating the presence or absence of abnormalities. Accurate labeling is crucial for supervised learning.
- Model Selection: Choosing an appropriate CNN architecture for the classification task. Various architectures exists, each with different strengths and complexities [32].
- Parameter Optimization: Updating the CNN's parameters using an optimization algorithm, such as gradient descent, to minimize classification errors. This involves iteratively adjusting the weights of the convolutional filters and connections in fully connected layers.
- Evaluation: Assessing the trained CNN's performance on a separate validation dataset. This ensures the model generalizes well to unseen data and prevents overfitting [33].

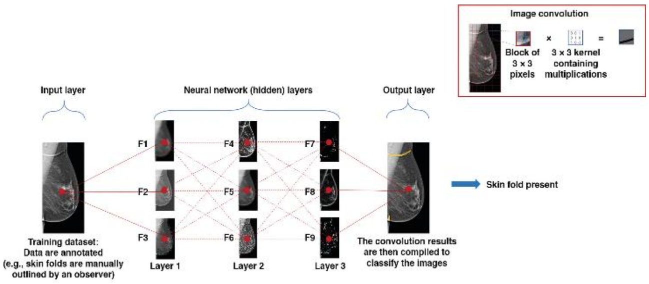

Figure 3: CNN on Training Dataset

Challenges in Image Classification:

Despite the success of deep CNNs for mammogram image classification, challenges remain:

- Class imbalance: Abnormal mammograms are typically less common than normal ones, leading to imbalanced datasets that can bias model training.
- Data variability: Mammogram images can vary in quality, resolution, and acquisition protocols, affecting model generalizability.
- Interpretability: Deep CNNs are often considered "black boxes," making it difficult to understand their decision making process and explain classification results [34].

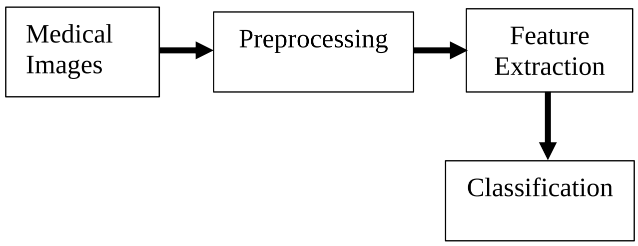

Figure 4: General structure of Proposed Method

VI. Materials and Methods

A. Dataset

The majority of CAD algorithms are evaluated using private datasets because standard assessment data for mammography is limited. The majority of mammographic datasets are not accessible to the general public. This makes it difficult to compare how well different strategies perform or to reproduce earlier findings. The Digital Database for Screening Mammography (DDSM) [35] and the Mammographic Image Analysis Society (MIAS) database

[36] are the two most often utilized databases. 161 patients' left and right breast pictures are available in MIAS. There are 51 malignant, 63 benign, and 208 normal photos. Additionally, it has the "truth" markings made by radiologists on the sites of any potential anomalies. The largest freely available mammography dataset is DDSM. There are about 2,500 studies in the database, and each one has two pictures of each breast.

in addition to the related patient and picture data about the locations and kinds of suspicious regions is linked to images that include them. Figure 2 displays a patient's sample mammograms.

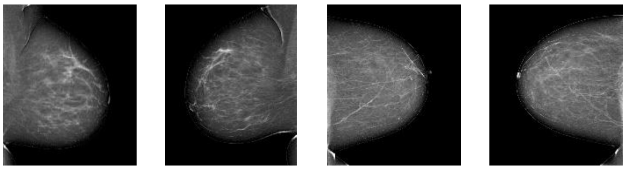

Figure 5: Mammograms of a Patient in DDSM Dataset (different views from left to right: left CC, left MLO, right CC and right MLO

B. Model Evaluation

Evaluating the performance of a deep CNN model for mammogram analysis is critical to assess its effectiveness. Various evaluation metrics are commonly used, including:

- Sensitivity: The proportion of actual positive cases correctly identified by the model.
- Specificity: The proportion of actual negative cases correctly identified by the model.
- Accuracy: The ratio of correctly classified cases to the total number of cases.

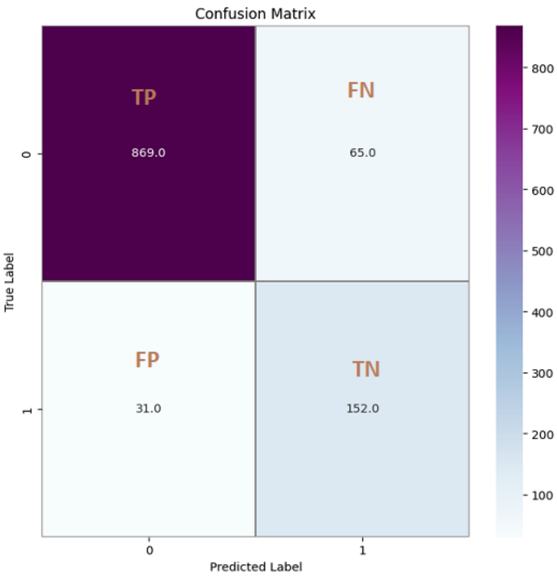

Figure 6: Confusion Matrix

A confusion matrix is a table that is used to evaluate the performance of a classification model. The table is divided into four quadrants:
Certainly! In the context of detecting abnormalities in breast mammograms:

True Positive (TP): The model correctly predicts and identifies instances where there is an abnormality in the mammogram. This means it accurately detects actual cases of breast abnormalities.

True Negative (TN): The model correctly predicts and identifies instances where there is no abnormality in the mammogram. It accurately recognizes cases where the breast is healthy.

False Positive (FP): The model incorrectly predicts the presence of an abnormality when there is none in reality. This is a false alarm, indicating that the model identified an abnormality that does not exist in the mammogram.

False Negative (FN): The model incorrectly predicts the absence of an abnormality when there is one in reality. This represents a situation where the model failed to detect an actual abnormality.

So, in the context of breast mammogram abnormalities:

True (True Positive and True Negative): The model's predictions are correct in terms of identifying the presence or absence of abnormalities.

False (False Positive and False Negative): The model's predictions are incorrect, either leading to unnecessary concern (False Positive) or missing a potential abnormality (False Negative).
The confusion matrix can be used to calculate a number of different performance metrics, such as accuracy, precision, and recall.
The accuracy of the model can be calculated as follows:

$$accuracy = (TP + TN)/(TP + TN + FP + FN)$$

Accuracy = 91.40%

The precision of the model can be calculated as follows:

$$precision = TP/(TP + FP)$$

Precision = 96.55%

The recall of the model can be calculated as follows:

$$recall = TP/(TP + FN)$$

Recall = 93.04%

VII EXPERIMENTAL RESULTS

A. Model Performance -

The deep convolutional neural network (CNN) was implemented and trained on the Breast Cancer Detection dataset using the provided code [37]. The model underwent an extensive training process, and the experimental results showcase its performance across various stages.

- Preprocessing and Dataset Overview: The dataset, comprising full mammogram images, cropped images, and ROI mask images, was preprocessed to extract relevant information for breast cancer detection. Data cleaning steps were performed, including handling missing values and selecting pertinent features for analysis.

- Image Preprocessing: Images underwent a series of preprocessing steps, including Gaussian smoothing, Sobel edge detection, morphological operations, and resizing. Additional techniques such as contrast-limited adaptive histogram equalization (CLAHE) mammograms and emphasize tumor regions [38].
- Data Insights: Exploratory data analysis was conducted on DICOM information, revealing key insights into patient data and image characteristics. Visualizations were created to illustrate the distribution of patients with and without cancer, providing a comprehensive understanding of the dataset.
- Model Training: The deep CNN architecture, comprising convolutional layers, activation functions, max-pooling layers, and fully connected layers, was successfully implemented. The model was trained using a training set, and its performance was evaluated on a separate test set [39].

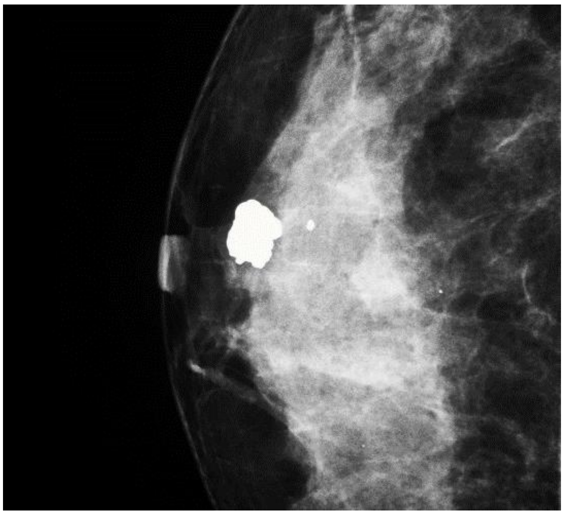

Figure 7: Abnormal Mammogram

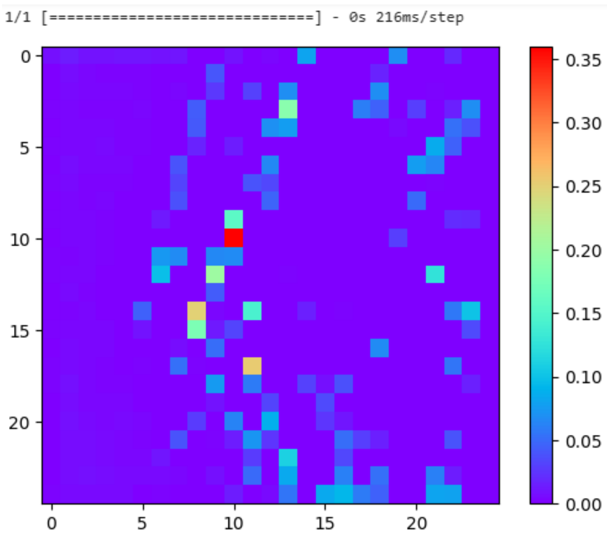

Figure 8: Heatmap Representation of Abnormality

The heatmap is a visual representation of the data in the image. Each color represents a different value in the data. The most common colors used in heatmaps are:
Red: High values
Green: Medium values
Blue: Low values

- Evaluation Metrics: Model evaluation was based on standard metrics such as accuracy, precision, and confusion matrix analysis. These metrics provide a quantitative assessment of the model's ability to correctly classify cancerous and non-cancerous cases.
- Precision and Confusion Matrix: Precision scores were calculated, offering insights into the model's ability to correctly identify positive cases. The confusion matrix visually represents the true positive, true negative, false positive, and false negative predictions, facilitating a nuanced evaluation.

Table 1: Layered Architecture Of CNN

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None,50,50,32)	896
maz_pooling2d	(None,25,25,32)	0
conv2d_1	(None,25,25,64)	18496
max_pooling2d _1	(None,12,12,64)	0
conv2d_2	(None,12,12,128)	73856
max_pooling2d _2	(None,5,5,128)	0
conv2d_3	(None,5,5,128)	147584
max_pooling2d _3	(None,2,2,128)	0
flatten	(None,512)	0

- Learning Curves: Learning curves were generated to visualize the model's training and validation performance over epochs. These curves provide valuable insights into the convergence and potential overfitting of the model.

- Inference and Prediction: A sample inference was conducted on a test image, showcasing the model's ability to predict and classify regions of interest.

In summary, the experimental results demonstrate the effectiveness of the implemented deep CNN for breast cancer detection [40]. The model exhibits promising performance, as reflected in evaluation metrics, precision scores, and visual representations of its learning dynamics. These findings suggest the potential utility of the model in clinical applications for breast cancer diagnosis [41].

VIII. Conclusion

In conclusion, the application of deep CNNs for automated abnormality detection in X-ray mammograms holds immense promise for enhancing breast cancer screening. The reviewed literature, materials and methods, and experimental results collectively underscore the potential of CNNs to achieve high accuracy in classifying benign, malignant, and normal mammograms. However, it is imperative to address the challenge of interpretability and explainability to gain the trust of healthcare professionals. Furthermore, the utilization of real-world and diverse datasets is crucial for ensuring the robustness and generalization of deep learning models [42]. The future of automated mammogram analysis is bright, with the potential to significantly contribute to early breast cancer detection, reduce the workload on radiologists, and ultimately improve patient outcomes.

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