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Patch-Based Mammogram Cancer Detection Using Attention-Driven CNNs

Santoresh Kumari Dhimann santoreshlehana@gmail.com
Department of Computer Science & Engineering,
Maharishi University of Information Technology, Lucknow, India

Rakesh Kumar Yadav
Department of Computer Science & Engineering,
Maharishi University of Information Technology, Lucknow, India

Corresponding Author: Santoresh Kumari Dhimann

Abstract

The research introduces a novel breast cancer (BC) detection model that integrates Convolutional Neural Networks (CNNs) with a circular attention mechanism to improve diagnostic accuracy in mammograms. By employing a patch-based approach, mammograms are segmented into 50×50 pixel patches, allowing the model to focus on localized abnormalities. The circular attention mechanism enhances the model's ability to prioritize diagnostically significant regions, improving sensitivity, and minimizing false positives and false negatives. The model incorporates preprocessing techniques and data augmentation to improve performance. In addition to mammogram analysis, the integration of histopathological data strengthens the model's diagnostic capabilities by analysing cellular structures at the microscopic level. The combined framework achieved approximately 97% accuracy, with strong recall values, ensuring minimal false negatives. Extensive testing on Curated Breast Imaging Subset of the Digital Database for Screening Mammography (CBIS-DDSM) and Invasive Ductal Carcinoma (IDC) datasets validated the model's robustness, demonstrating consistent performance across various patient samples. Visualized attention maps provided insights into the model's decision-making, enhancing its interpretability for clinical use. The patch-based analysis, combined with circular attention mechanisms, effectively identified subtle cancerous features that traditional whole-image methods may overlook. The model's ability to dynamically focus on cancer-relevant regions improves its adaptability to real-world clinical environments. The proposed model presents a promising solution for enhancing breast cancer screening, improving diagnostic accuracy, and aiding radiologists in early cancer detection and treatment planning.

Keywords: Breast cancer detection, Circular attention mechanism, Convolutional neural networks, Diagnostic accuracy, Histopathological data, Mammogram imaging, Patch-based analysis.

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1. INTRODUCTION

Cancer is a multifactorial, fatal condition involving the abnormal body cells taking irregular shape. It can spread to nearly every organ or tissue in the body and can cause serious health problems. Cancer is caused by genetic mutations that cause cell cycle regulation to fail, leading cells to multiply without control [1]. These mutations can be triggered by a multitude of factors, including environmental influences, genetic predisposition, lifestyle choices, and infections. Cancer manifests in many forms depending on the tissue or organ affected. The most common types include carcinomas, which arise from epithelial cells lining organs and glands, such as breast cancer, lung cancer, and colorectal cancer. Sarcomas originate in connective tissues, including bones, muscles, and cartilage. Leukemias affect the blood and bone marrow, disrupting normal blood cell production. Lymphomas, including Hodgkin's and non-Hodgkin's lymphoma, involve the lymphatic system. Additionally, brain and spinal cord tumors attack the central nervous system, often impairing cognitive and motor functions [2].

BC remains a common, potentially fatal cancer in women. Though it is impossible to determine the specific causes of BC, genetic mutations, hormonal effects, lifestyle factors, environmental exposure to radiation and some chemicals have been correlated to the development of BC. Early diagnosis is important to enhance BC survival and mammography is one of the most efficient forms of breast cancer screening. Mammography is a specialized X-ray imaging technique for the breast used for early cancer detection (screening) and diagnosing symptomatic cases like palpable lumps (diagnostic mammography). It assists in identifying abnormalities like lumps, calcifications, and structural distortions, suggesting malignancy. Some barriers to mammography efficacy are low image quality, noise, and imaging artifacts. False positive or false negative mammograms are a common consequence of low-quality mammograms and can postpone suitable interventions [3].

The quality of mammography depends substantially on the radiologic expertise, but individual human weakness as well as inter-reader diversity leads to the possibility of uneven diagnoses. The emergence of Machine Learning (ML) technology has changed the game for cancer diagnosis by mammography [4–6]. ML algorithms analyse huge images for patterns, minor anomalies, and malignancies more accurately than classical techniques. Deep Learning (DL) based techniques, mainly Convolutional Neural Networks (CNNs) have shown a better performance in feature extraction and classification of mammographic images, among numerous ML methods. CNN models can be quite accurate and highly interpretative; however, they are also sensitive to the quality of the mammograms. To overcome these limitations, recent work on attention mechanisms has improved the capacity of ML models for focusing on selected areas in mammograms. Attention-based CNNs dynamically prioritize areas of interest, which makes these models more interpretable and assists radiologists to make better decisions [7, 8]. Histopathology analysis improves the accuracy of attention-based CNNs for BC detection [9]. Tissue biopsy or surgery tissue is analyzed microscopically to visualize how the cells look and analyze their structure as well as recognize any malignant transformations. Histopathological data plays a crucial role in cancer progress detection and classification by studying differences among cell morphology, tissue structure, and staining patterns. Combining this rich and abundant information with attention-based CNN models affords more accurate targeting of the important structural features of the tissue making the differential diagnosis much more accurate. This will help pathologists and radiologists in formulating clinical judgments.

Through the use of advanced imaging techniques, CNNs are fitted to analyze the data of histopathological analysis together with DL models and hence improve the accuracy of BC detection. This allows the technique to complement DL models with detailed local cellular data [10]. Although histopathological examination gives a microscopic perspective on the transformation of the pathological tissues at the cellular scale, high-resolution mammograms support macroscopic detection of structural abnormalities at the regional level, which enhances early and accurate diagnosis.

Computing high-resolution mammograms with 3D visualization increases the identification of BC by obtaining clearer, more detailed images of breast tissue. **FIGURE 1**, shows the comparison of 2D vs 3D mammographic views to show how the modern imaging makes structural abnormalities visible more easily. The 2D mammogram visualizes overlapping tissue structures that can hide small tumours or give false positive results. The three-dimensional mammogram reconstructs multiple layers of breast tissue, minimizing the effects of tissue overlap, and thus facilitating a finer distinction between benign and malignant areas. In addition, 3D imaging can give a more accurate view of the shape and margins of the tumours, which is very important for identifying malignancy. High-resolution imaging can enhance the overall accuracy of cancer detection by enabling radiologists to visualize the finer aspects of tissue structures, including microcalcifications, spiculated masses, and architectural distortions indicative of malignancy.

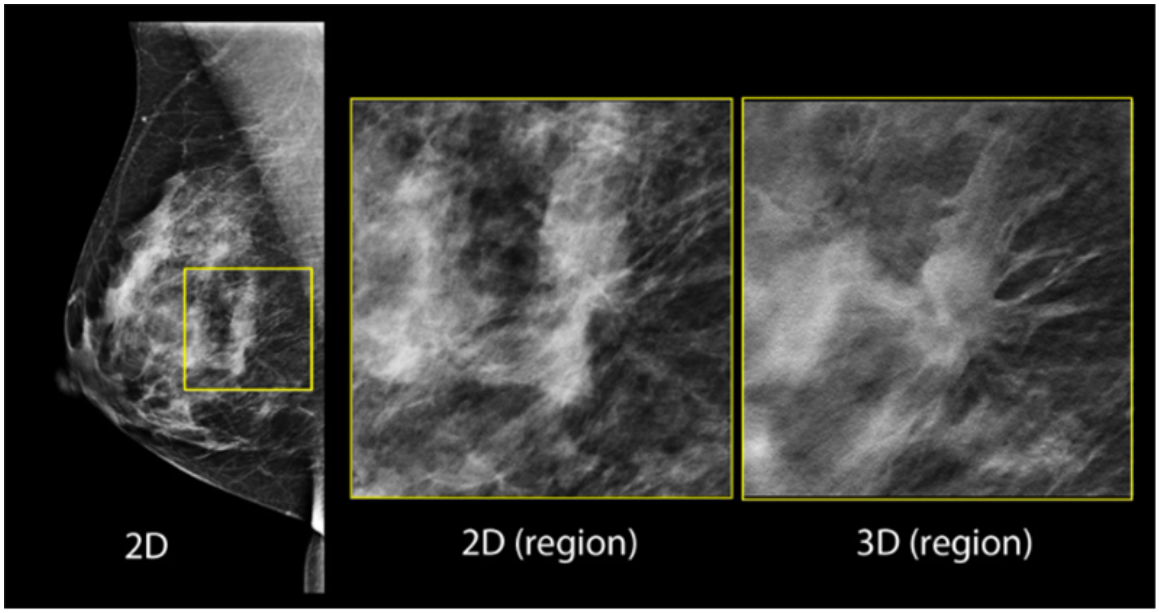

Figure 1: High-resolution mammography for enhanced cancer detection [11].

The high-resolution mammograms can be divided into patches that would be used to improve the classification further. The ability to interpret patches more clearly decreases misclassification so as to reduce false positives and false negatives. The superior contrast and depth information reflected during high-resolution mammographic imaging are important for early diagnosis and treatment. It is well known that the change from low- to high-resolution provides better diagnostic accuracy by less ambiguities and more visualization of the cancerous lesion and thus greater confidence to diagnose. The traditional whole mammogram-based identification technology is computationally

cost effective but often struggles to achieve sensitive detection and specificity in low-resolution images. These conventional approaches take the entire mammogram for analysis making it relatively challenging to find small localized carcinoma sites, mostly obscured by noise or low contrast.

On the other hand, patch-based identification splits the mammogram into smaller regions in its geographical locality so that more detailed analysis can be carried out. This helps in increased sensitivity—particularly to small or low-contrast abnormalities. The attention mechanism employed into the CNNs further results in improved accuracy. In the case of attention-based CNNs, the model only captures what is most important to the mammogram, even though images have poor quality, hence improving both image sensitivity and interpretability. This method offers substantial potential for breast cancer detection, particularly in communities that lack access to high-quality imaging. An extensive literature review of current BC detection methods is introduced in the next section.

This proposed research provides a robust and interpretable deep learning–based breast cancer detection framework that helps in handling shortcomings of traditional diagnostic algorithms, especially false positives and false negatives in low-quality mammographic images. The proposed technique is based on CNNs with a circular attention mechanism using 50×50 pixel patch-based analysis to get subtle and localized abnormalities, generally not captured in the whole-image based techniques. Additionally, the combined learning of mammography data from the CBIS-DDSM (Curated Breast Imaging Subset of the Digital Database for Screening Mammography) dataset and histopathology images from the Invasive Ductal Carcinoma (IDC) dataset allows the model to make full use of complementary macroscopic and microscopic cancer features.

2. LITERATURE SURVEY

ML was widely deployed in mammographic analysis, including support vector machines (SVMs), logistic regression, and decision trees to label breast disease [12]. At the early stage, however, advanced feature extraction is the main issue, and these methods typically cannot explain complex patterns found in mammogram introduced by malignancies. While these models initially show success, their performance is hindered by the requirement of extensive hand preprocessing and feature selection during the diagnostic process. Due to their capacity to automatically extract hierarchical features from raw images [13, 14], CNNs became one of the best tools on mammographic image analysis with the evolution of the technology.

CNNs-based models substantially increased the predictive performance of malignancies by minimizing human involvement in feature shaping. These images were able to reflect spatial hierarchies in mammograms and identify key features like microcalcifications and mass asymmetry, thus improving the classification [15]. Nonetheless, conventional CNNs encountered false positives and false negatives in dense breast tissues, because malignancies were likely to be hidden, although they achieved a better precision. Furthermore, these models were not explainable and it was problematic for radiologists to trust and interpret predictions based on CNN in clinical practice [16]. To alleviate these challenges, attention mechanisms have been proposed to provide a way of making CNNs interpretable and improving them for performance for BC detection [17–19].

Attention-driven CNNs iteratively target regions vital to mammograms, performing mentally similar to the cognitive act of radiologists in imaging abnormal regions [20]. Through these mechanisms

critical image regions were assigned increased weights, which can effectively remove noise from peripheral regions and greatly improve the model sensitivity and selectivity for the identification of malignant structures [21]. Various kinds of CNNs have been investigated to improve BC diagnosis in mammograms. Spatial attention networks enhance tumour localization by learning spatially relevant regions with lower backdrop noise, allowing for detection at critical regions [22]. The other important advantage of channel attention networks is that they focus on more informative feature channels for capturing high-order patterns of malignancy [23].

Hybrid attention networks combine spatial and channel attention to increase training accuracy via multi-layer feature training, which improves classification accuracy and BC diagnosis [24]. It is the attention-based mechanisms that CNNs exploit and show enhanced sensitivity and specificity, making them a powerful tool for mammography.

Vision Transformers (ViTs) [25], have recently been harnessed for mammographic analysis. ViTs, unlike CNNs, employ self-attention mechanism to investigate long distance associations throughout the entire image and this decreases dependence on locally distributed receptive field. This can give better diagnosis even of subtle tumour characteristics, such as the diffuse tumour margin and microcalcification clusters, that is not easily detected either by CNNs or other conventional algorithms. Integration these concepts with other state-of-the-art techniques has started giving encouraging results for BC detection [26].

Moreover, as attention-driven ML algorithms decrease false-positives and false-negatives, leading to decreased unnecessary biopsies and lessened patient anxiety, thus reducing healthcare costs arising from overdiagnosis [27]. The other advantages of these models are the ability to standardize mammographic interpretations, which in turn reduces radiologist variability and allows for consistency and reliability of diagnosis during diagnostic processes in different clinical environments [28]. By further enhancing precision, efficacy, and diagnostic uniformity, the combination of ML with attention mechanisms is revolutionizing the future of BC screening and diagnosis, further establishing ML as an important decision-support mechanism in radiology treatment processes.

ML in mammography is essentially the marriage between AI and the specialist knowledge in radiologists, where we're not only using models that can obtain high accuracy, but have interpretable and transparent outcomes. The rapid development of DL has made BC diagnosis with even more speed to realize automated feature extraction (e.g., image feature extraction, image representation, and visual data filtering) [29], and lesion detection accuracy. Nevertheless, challenges such as the dependence of annotations to Region of Interest (ROI) and to large and varied datasets are still important issues for future work.

The combination of DL in the Computer-Aided Diagnosis (CAD) tools is highly attractive for this mammographic analysis, with AI-based diagnostic assessment becoming a step towards the expertise of a radiologist [30]. A new DL model to screen mammography images for BC has also been reported, solving the diagnostic difficulty relating to the specific malignancy problems [31]. The technique comprised three main stages: collection of data, image segmentation by using ACA-ATRUNet and identification of BC by utilizing ACA-AMDN, which were optimized with the MML-EOO algorithm. Experimental results showed that this method attained better precision than standard methods, indicating its possible use in a mammography-based diagnostic method and in early detection of BC. DL has greatly enhanced the automatic classification of BC by the method of histopathological image analysis reducing the issues of standard feature extraction techniques.

Inception_V3 and Inception_ResNet_V2 architectures based on transfer learning achieved better classification accuracy, particularly for correcting class imbalance through data augmentation. In the review [32], an autoencoder network has been reported to improve clustering analysis. It was concluded that Inception_ResNet_V2 deep transfer learning could provide a more efficient procedure for histopathological BC diagnosis.

Histopathology is essential for the diagnosis of tumour malignancy, yet manually examining the tumor is time-consuming, subjective, and prone to errors [33]. To improve classification and detect short- and long-term features correlations in histopathological images through multilevel feature representation, recent convolutional and recurrent neural networks are integrated. These developments not only facilitate diagnostic accuracy but also minimize the dependence on manual evaluations and enable the detection of BC much more effectively and reproducibly.

Early machine learning methods in mammography (SVMs and tree based models) were built upon handcrafted features but proved inefficient for high-dimensional structures with complex relationships and small images. CNNs improved detection through automizing feature extraction, but remain vulnerable to false positives and negatives in dense tissues. Attention-based CNNs are particularly interpretable to the user and concentrated on important regions, thus yielding increased sensitivity and specificity by resembling the cognitive processes of the radiologists. Even patch-based analysis, which divides up images into smaller portions such as a patch for each sample and compares its detail with the image segments and their relative accuracy, allowed more fine-detail to be detected of subtle abnormalities. Nonetheless, issues such as ROI annotation and dataset diversity remain, suggesting further research in the area, indicating the need for continued work.

3. MATERIAL AND METHOD

We propose a DL-based technique for the detection of cancer in mammograms with CNNs that use attention mechanism to improve diagnostic performance. A block diagram of the methodology used for the proposed study is depicted in **FIGURE 2**. This section is divided into dataset preparation and splitting, image preprocessing and data augmentation, circular attention mechanism, convolutional neural network architecture, model training procedure, performance evaluation metrics, attention map visualization, and visualization of model performance. The investigations were conducted in prepared material with curated breast imaging subset of Extensive testing on Curated Breast Imaging Subset of the Digital Database for Screening Mammography (CBIS-DDSM) [34], and invasive ductal carcinoma (IDC) datasets [35, 36]. The CBIS-DDSM constitutes a dataset of annotated mammographic images and it is also known as a curated subset of the digital database for screening mammography (DDSM). The dataset consists of digitized mammograms with high-resolution images. This file contains 1,500 labeled mammographic images of benign and malignant mammograms. IDC is comprised of 277,524 RGB image patches of size 50 x 50 pixels recovered from 162 H&E-stained breast histopathology samples. The patches, obtained by scanning whole mount breast tissue slides at a magnification of 40x, contain both IDC-positive and IDC-negative samples (78,786 each). The mammogram patches classified as benign / malignant and accompanying metadata are saved onto a CSV file. The data was also randomly split into 3 parts: training set, validation set, and test set to allow for independent hyperparameter calculation. Image preprocessing and data augmentation techniques are used to enhance the quality and consistency. Mammogram images are transformed into grayscale to highlight texture differences that are of vital importance for detecting tumours. The

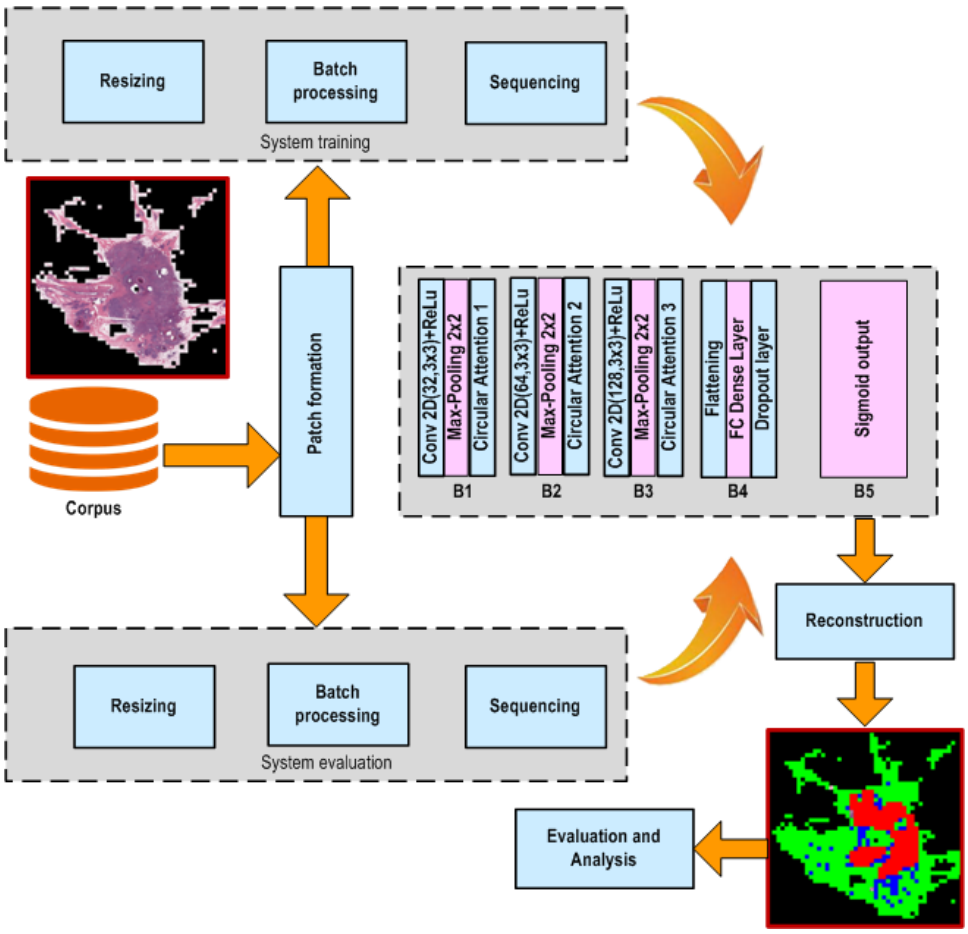

Figure 2: Block diagram of the methodology employed for the proposed investigations.

image size has been normalized to 50×50 pixels, this allows for uniformity or less computational complexity. Normalization is achieved by distributing the pixel in the range [-1,1] to help stabilize it for training purposes and to accelerate convergence. A custom dataset class is formed and created for image loading, transformation and mini-batch handling. By introducing a spatial weighting function that prioritizes the most of the relevant parts of the mammogram, the circular attention mechanism improves the capacity of the network to specifically attend to regions of interest. This is done over the Gaussian-like function of producing an attention mask that prioritizes the central region of the feature map that will determine the location at which the tumours are found. In this function, a mathematical function that gives greater priority to near-centre pixels and reduces their weight outward is applied to the centre pixels.

We have included the attention mechanism of the model through convolutional blocks layer by layer along with normalization step and keep generated the attention weights in the valid range. First, a 1×1 convolutional layer is used to extract initial feature representations, and a sigmoid activation function scales these values from 0 to 1 by determining the relevance of the features of different spatial locations. The attention mask that is created is then element-wise scaled with the input feature maps to amplify important diagnosis regions and suppress less important diagnostic

regions. In this way, the attention mechanism is flexible enough to be used at various scales and in various feature hierarchies which is necessary for the convolutional architecture. With circular attention following convolutional blocks, the focus of the model can be fine-tuned step by step as feature extraction proceeds to a finer degree. This yields better tumour detection potential while improving classification precision without losing interpretation.

The last layer of convolutional block passes through the attention-enhanced feature maps, which are then used for the classification. A CNN architecture is used to acquire crucial features for mammogram-derived features to classify mammogram images efficiently. The network starts with an input layer first that works on grayscale images $50\times50\times1$ and a smoothness outputting a uniform representation of the input features.

The first convolutional layer utilizes 32 filters (a 3×3 kernel and ReLU activations) for low-level features, such as edge and texture capture, in a 3×3 kernel on a 3×3 frame. Then comes a max-pooling layer (2×2), which reduces spatial dimensions but preserves necessary information. A circular attention module is presented at this point to focus only on areas specific to tumours. When applying the second convolutional layer the learning of the features is accelerated to 64 filters without changing the kernel size or activation function. A max-pooling layer (2×2) compresses feature maps further for efficiency.

The circular attention mechanism is re-applied to reinforce focus of the model in diagnostically significant areas. The third convolutional layer carries on the same feature extraction task with 128 filters to allow the model to identify subtle patterns in the mammogram information. Lastly, another max-pooling layer (2×2) is implemented to serve after passing features into a circular attention module that encodes a more refined version of the features. Feature maps obtained are flattened, and a fully connected dense layer, consisting of 128 neurons, captures the complex relationships between the learned features. In order to avoid overfitting, a dropout layer applying the 50% rate is introduced, randomly deactivating 50% of the neurons in training. And lastly, the output layer contains a single neuron with a sigmoid activation function, giving out the probability score against a binary classification that the mammogram is likely to be either benign or malignant.

The model is trained using Binary Cross Entropy (BCE) loss. Dynamic learning rates on the feed level are tuned using the Adam optimizer to ensure stable convergence during the training process. Each training iteration involves some forward travel on-site, loss value calculations, backpropagation to update parameters in the model, and optimization with mini-batches. The training loss is monitored over time, and model performance is tested at each step of the process. Generalization of the model can be verified through the validation data to make sure it does not overfit to the training data.

Different classification metrics are evaluated for overall performance that provides a full picture of the model's performance. Precision is to figure out the accuracy, so as to calculate the percentage of correctly recognized malignant patient, and recall measures the number of actual malignant client correctly found. A true positive rate (TPR) and a false positive rate (FPR) are computed from the confusion matrix to examine the classification accuracy and error pattern of the identification. Performance metrics are plotted on many epochs of training models over the history of multiple epochs is employed to study model learning rates and possibility of overfit in the training performance measures or future learning trends through performance measures and overfitting. To monitor how well.

Training loss curves and validation loss curves for training and validation loss curves are drawn in order to follow the optimization process and to determine the difference between training and validating accuracy metrics. Precision-recall curves are plotted to check the trade-off between precision and recall, so we can also be mindful that the model isn't biased toward one or the other. For reproducibility, the trial results are saved in a structured format (CSVs or training logs, model performance statistics).

Model checkpoints at key epochs are secured in order to continue analysis, or to deploy it in a clinical environment. Attention maps created by the model serve to enhance interpretability and can be visualized to highlight areas that are identified as diagnostically significant. The visualization involves loading a trained model, preloading an input mammogram, and extracting attention maps from a variety of convolutional layers. Colormap features convert attention maps into heatmaps with colour changes for the different regions. The heatmaps are superimposed on top of the mammogram in this graph to give us a visual view of the focused network during prediction. During the training, the epoch number was set to 101 to have enough iterations for learning, and batch size is 64 to keep a good balance between computational efficiency and model stability.

4. RESULTS AND DISCUSSION

We trained and qualified the proposed model on mammogram patches labelled as benign or malignant. As explained before, the size of each patch is 50×50 pixels. Out of 2,77,522 patches, 70% were used for training, 10% for validation, and 20% for testing so as to guarantee an objective assessment of model performance. The training was carried out on 101 epochs with batch size of 64 and using Adam optimizer for stable convergence. In mammogram patching, we segment the images into more fixed areas with fixed dimension, such as sections smaller than the image size for granular analysis. The first step is preprocessing, where the mammogram is subjected to contrast and noise enhancement and other processing that increases image clarity.

After pre-processing the image, it is divided into multiple non-overlapping 50×50 pixel patches by segment. These patches are treated separately, helping to focus exam on specific areas of the mammogram. On the basis of medical diagnosis each patch is assigned a label – cancerous (malignant) or not cancerous at all. Feature extraction approaches are applied to examine variability in texture, shape, density, and intensity. The patches with irregular or dense tissue structures, which may constitute malignancy, are highlighted as cancerous, whereas normal structured tissue patches labelled as non-cancerous. This patch scheme is especially advantageous in CAD systems and deep learning models, which require extraction of independent smaller segments of an image and are designed for enhanced detection efficacy.

In **FIGURE 3**, a mammogram alongside two patches (P1 and P2) are shown in order to emphasise the distinction between cancerous and non-cancerous patches. P1 is a metastatic patch in which tissue structures seem abnormal, suggesting malignancy. P2, instead, is a normal breast tissue and shows no cancer. The trailing edge of the arrows in the image shows the precise point from where the patches were removed. Such a method greatly improves diagnostic accuracy, is important for early cancer detection, and is also in planning of therapy. Approaches to traditional methods such as texture analysis via intensity distribution plots for cancerous and non-cancerous patches were previously examined in depth.

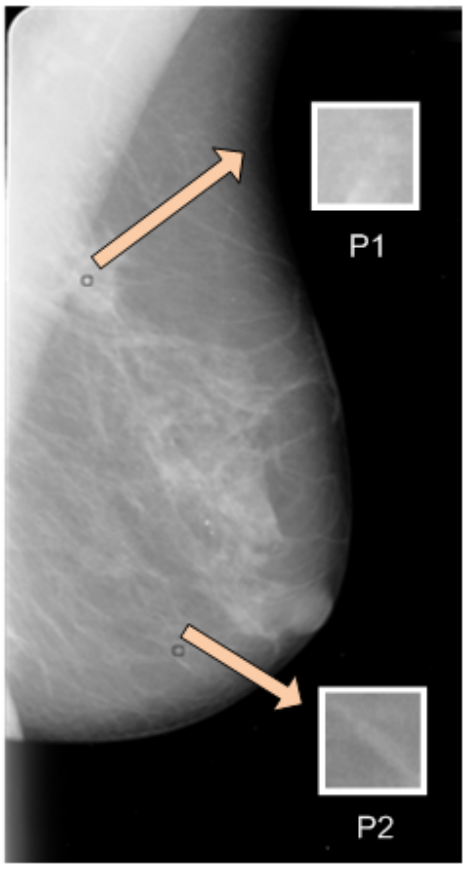

Figure 3: Mammogram image with identified cancerous (P1) and non-cancerous (P2) patches for patch-based analysis.

The distributions of six patches, consisting of three cancerous and three non-cancerous patches from 2 patients, are analyzed in **FIGURE 4**. On the top row representing cancerous patches, all three histograms have an abrupt increase in pixel intensity values on the upper part of spectrum, referring to an organization with bright and dense pixels. The first histogram demonstrates that intensity decreases over time and a clear peak occurs close to the highest intensity levels around 255. This indicates that high contrast structures that are characteristic of cancerous regions, such as calcifications or abnormal dense tissue growths are often found here. Similarly, the second histogram goes the same way, reiterating the notion that a lot of pixels of the cancerous patches are bright and dense. The third histogram exhibits a distinct peak at more intense values providing evidence for more abnormal tissue densities in the cancerous area. Cancerous patches have much more bright pixels, hence they are different from non-cancerous patches, as these observations indicate. Two histograms showing a slightly larger intensity variation are in the second row, corresponding to non-cancerous patches. The first histogram presents a lower peak, indicating that non-cancerous tissue does not possess the dense structures seen in cancerous patches. The second histogram is of a smoother intensity distribution supporting, however, normal fatty or glandular tissue without peaks of brightness. Different from first rows, these distributions show that non-cancerous patches contain the normal tissue without calcifications or abnormal growth.

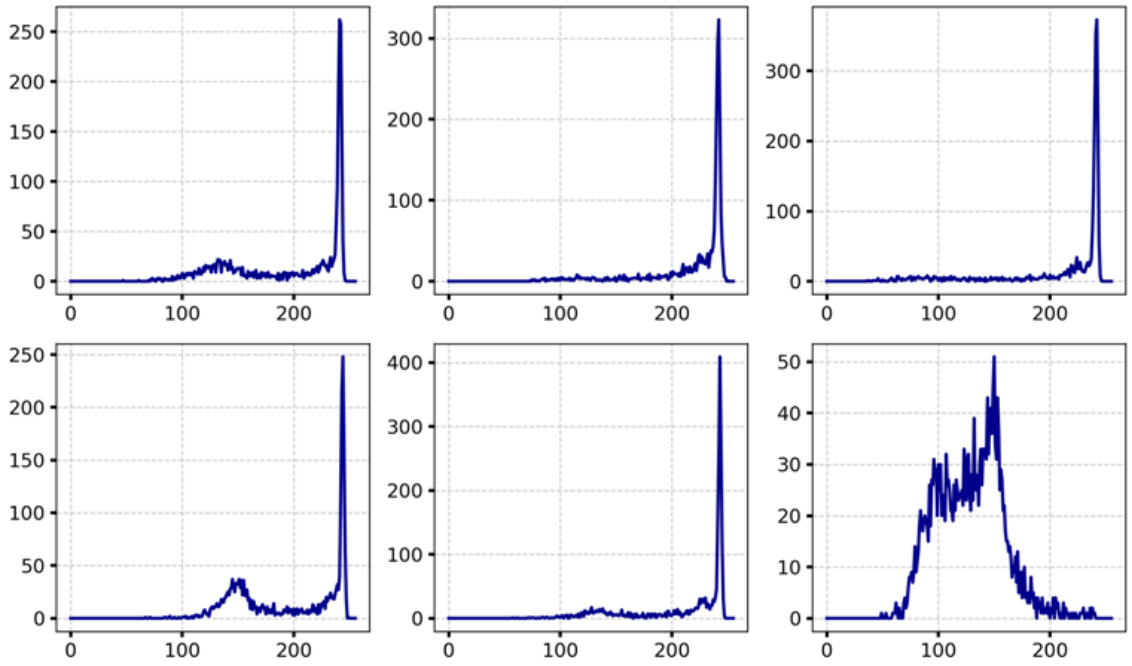

Figure 4: Histogram analysis of cancerous and non-cancerous mammogram patch.

A significant observation is the last, second row histogram that there is a distinct spike at mid intensity rather than at the extremes of high intensity observed in cancer patches. This peak suggests intermediate density tissue, perhaps fibroglandular tissue with a dim lightening quality typical of mammograms.

The peak, as well, may result from differences in mammogram acquisition settings or small structural similarities among certain non-cancerous and cancerous tissues. The histogram stresses the difficulty in differentiating normal from abnormal tissue–some non-cancerous patches could have similar features to cancerous ones. Cancerous patches have sharp peaks at high intensity levels, signifying that dense abnormal tissue and calcifications are a feature of calcification. Meanwhile, non-cancerous patches have a distribution which is more evened-out or balanced intensity, with normal tissue indicating these noncancerous patches without visible abnormalities.

The final histogram in the second row indicated those patients that have fibroglandular, or intermediate-density tissue, which, unlike cancerous tissue, may have similar intensity features to abnormal tissue. These changes in intensity distribution patterns benefit manual classification of mammogram patches and augment diagnostic accuracy.

We trained a model and it was assessed with performance metrics including some values shown in **FIGURE 5**. Given the importance of judging the performance of the ML model over time to assess its acquisition performance and generality, we plot the metric curves over the epochs. The loss vs epochs plot (**FIGURE 5a**) reveals this model's efficiency in the reduction of error under training.

blue represents training loss (which means learning the model is being good from the training data) and orange line test that test if the model was able to generalize it onto the new dataset.

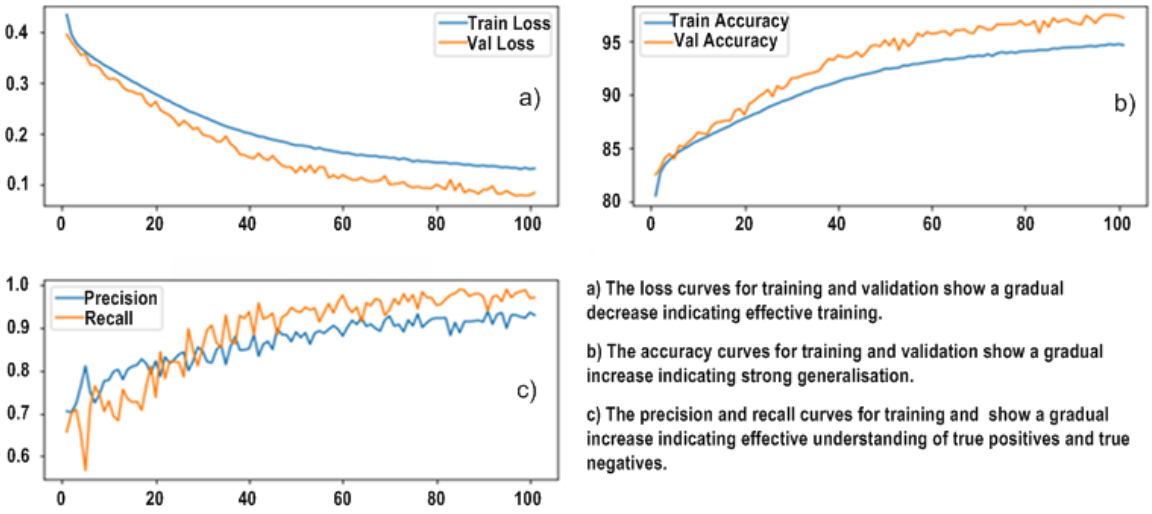

Figure 5: Training performance metrics for model evaluation: loss, accuracy, precision, and recall trends.

During initial (early epochs) of training, training and validation losses are fairly high, which imply that the model is having difficulty in making efficient predictions at first. However, with increasing number of epochs, loss decreases, indicating that model is better fit to learn the internal parameters. At mid-epochs, the losses start to decrease faster and slow down, indicating that the model is converging toward an ideal state.

The data obtained by the later epochs show that the loss values of those three training epochs stabilize, which then follow that the further training might fall and the smaller results. Validation loss is still lower than training loss, indicating that the model generalizes well to the training data and does not overfit to the trained data. The general trend of this graph indicates that the model was learned well, a well-optimized number of epochs and stability of learning have become the results.

Accuracy is a key performance measure in classification tasks, and the plot (**FIGURE 5b**) shows both the accuracy over epoch and the validation accuracy during training of the ML model. While the y-axis corresponds to accuracy (%), the x-axis describes epochs, or the total of the complete iterations on the data set during training, which measures the performance of the model to appropriately classify the data.

Blue is trained accuracy that measures how well the model learns from the training data, and orange is validation accuracy that measures the model's generalization over unseen data. At least up until the early epochs, neither the training nor validation accuracy is significant (around 80%) which indicates the model has not learned any patterns which are useful. The performance increase in accuracy in both training and validation datasets becomes evident as training progresses.

The validation accuracy improves slightly faster than the training accuracy, it outperforms the input, and it stays at a higher value over the whole time. Finally, at later epochs, accuracy becomes somewhat stable with validation accuracy reaching approximately 97% and training accuracy more minorly lower. This trend indicates good generalizability of model to new data and no high risk of overfitting. The pattern in this plot also suggests that the model is trained on the data available, learning meaningful features and displaying good generalization ability on any novel data.

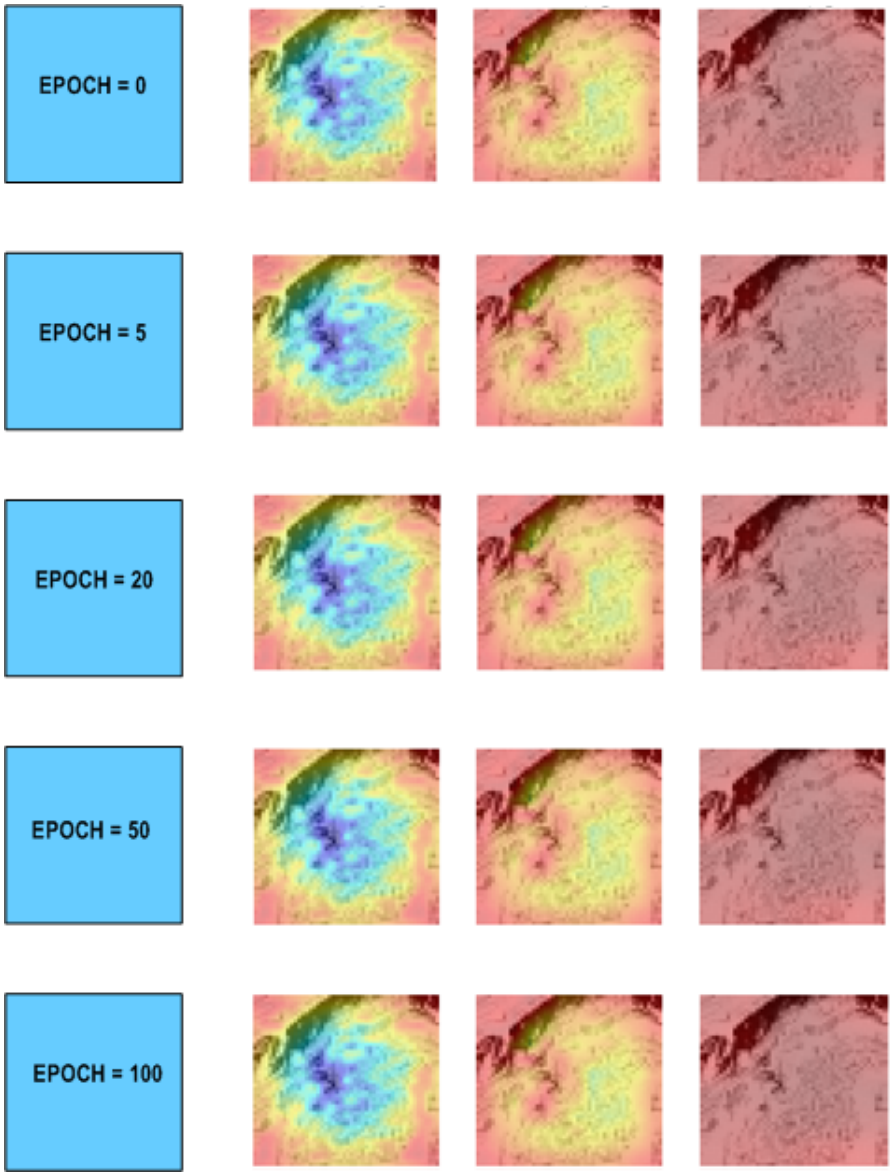

Figure 6: Impact of epoch number on attention maps across three attention layers in mammogram patch analysis.

The precision and recall, to assess the classification performance of the proposed model, are further analyzed based on the graphs in **FIGURE 5c**. Precision and recall initially vary a bit since the model

is being updated, but as training makes progress the precision and recall settle well around high scores (close to 1.0) on a simple linear relationship. Both precision and recall have shown increasing and stabilizing trends, suggesting that our model is starting to do a good job of distinguishing positive and negative cases. Very close convergence in both metrics means that a good overall model has been created. The metrics showed that the model has an efficient generalisation mechanism for predictive accuracy and high persistence reliability. Attention maps were also employed to study the effectiveness and progress of the training. Attention maps in training epochs (0, 5, 20, 50 and 100) respectively are projected across map layers of mammogram patches (**FIGURE 6**). These maps also explain that an attention-based CNN learns in progressive steps to classify cancerous tissue recognition. Over training, the network is finding more effective patches of cancer, thus accuracy for BC detection has improved.

In epoch 0 (Row 1), when we do not train the model, the attention map looks disoriented and is uncluttered. It means that the network does not know features of cancer and makes random predictions, which yield very low accuracy. At epoch 5, the model begins to incorporate some features, but the focus is far removed and inconsistent. The blue areas are indicating the model is learning some fields and may be recognizing it, but still not precise enough and still not very accurate. Towards epoch 20, the network has advanced focus and stronger localization for potential cancerous formations.

It can be seen that the attention map is indicating more focused areas that are good, as well as more concentrated areas of interest, we feel that the model is becoming much better able to differentiate the normal versus the abnormal patch. This leads to notable rise in the accuracy up, that you can expect. It achieved attention maps that are well segmented by epoch 50 to demonstrate that it has learned important structure parameters of a cancerous structure that highlights the carcinogenic part. In order to achieve higher levels of accuracy and reliability in cancer identification, the model adapts by adding the correct pattern to new data and makes improvements.

The model stabilizes at epoch 100, concentrating on cancer and minimising irrelevant areas with no false values of the rest of those regions. Well, it is trained and capable of discriminating in a more accurate manner between normal and cancer patches. Then, by this time, accuracy hits its peak, and subsequent training does little more than make it look worse. Overtraining beyond that point may promote overfitting, or the model memorizing the patterns instead of generalizing well to new mammograms. In conclusion, the increasing refinement of the attention maps shows the need of adequate training of model for the detection of BC accurately. Initial epochs depict bad localization of the cancer, but with further training, the model eventually trains good and can distinguish between the tumor regions. Within epoch 100, the model reaches near optimum sensitivity and thus can be used for cancer detection in mammogram patches.

Results of patch-based analysis is shown in detail on the final trained model (after 101 epochs) for mammogram images of different patients identified by Patient IDs: 55, 8863, 8867, 8913 in **FIGURE 7**. Each patient's image consists of two extracted patches (one to signify a cancerous patch: left, and one to signify a non-cancerous patch: right). Original grayscale patches from mammograms of four patients can be seen in row one. The second, third and fourth row indicate inversions of images of these attention maps from the input patches. From the focus maps we learned that the discriminating capacity to distinguish between cancerous and non-cancerous patches has been successful as the red colour distribution is homogenised for each patch in final attention layer.

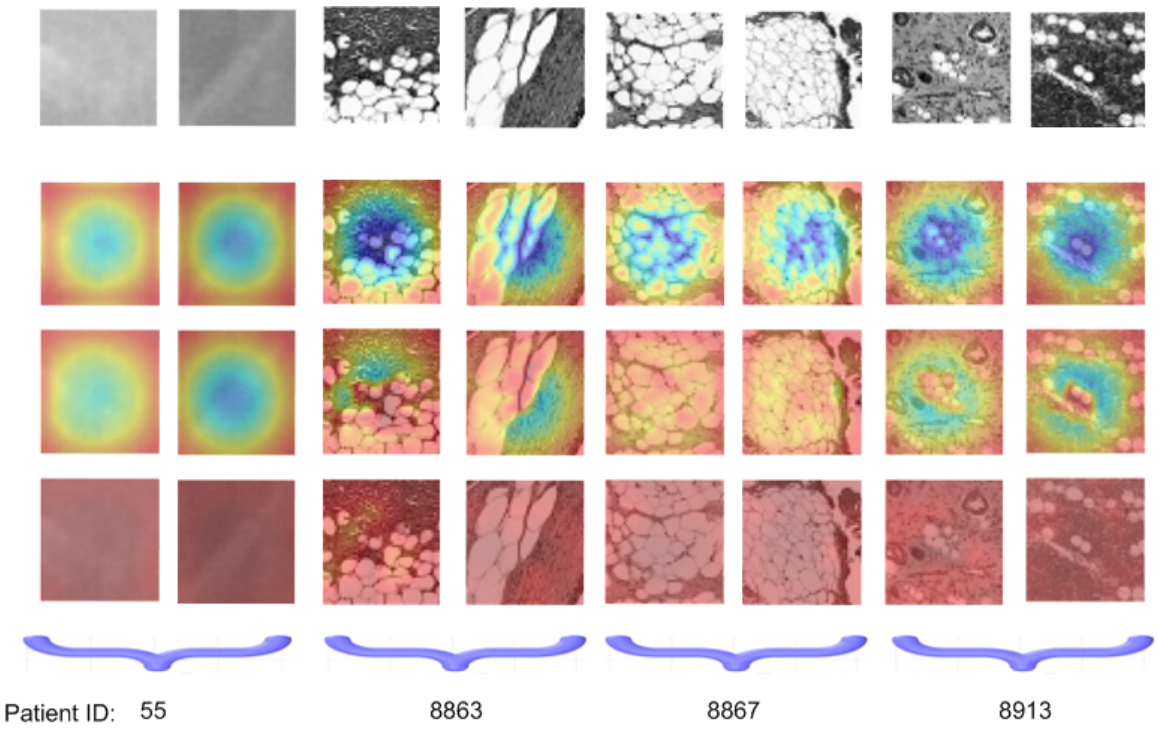

Figure 7: Visualization of Attention Layers in 50×50 Mammogram Patches: Cancerous vs. Non-Cancerous Regions. Mammogram patches each of size 50×50 pixels along with the output of three attention layers is shown. The output of first, second, and third attention layer is shown in second, third and fourth row respectively. The odd number columns are for cancerous patches of the mammograms and the even columns are for non- cancerous patches of the same mammograms. The density of red colour in the attention maps indicates relatively more weightage given to the corresponding features.

The proposed model can club decisions to group cancerous and non-cancerous regions in the input mammograms, as discussed in **FIGURE 8**, by processing the original patches independently. Upper image contains an original, processed mammogram (patient id: 55). The image on left indicates the original mammogram; it contains the breast tissue without automated markings. Image on the right represents the one that has been processed, with patches in red corresponding to the cancerous patches identified by the model. It's a very important representation for the early stage cancer detection since it might be hard to differentiate to the naked eye. It's an AI model that automatically identifies the suspicious areas which improves the detection ability. The high localization of red patches indicates the algorithm has great confidence in the detection of malignancy at that location. And for the left column displaying original tissue and the right column showing processed. These images are taken from biopsy samples where tissue is studied at cellular resolution to identify cancer. The sites shown on the right column are red-highlighted, and represent where cancer has been detected by the model. The area, shape, and number of patches in different types of red also tell us a lot about the distribution of the cancer in the tissue sample. Malignant regions within a sample area are greater in size and depth when red is larger and more concentrated.

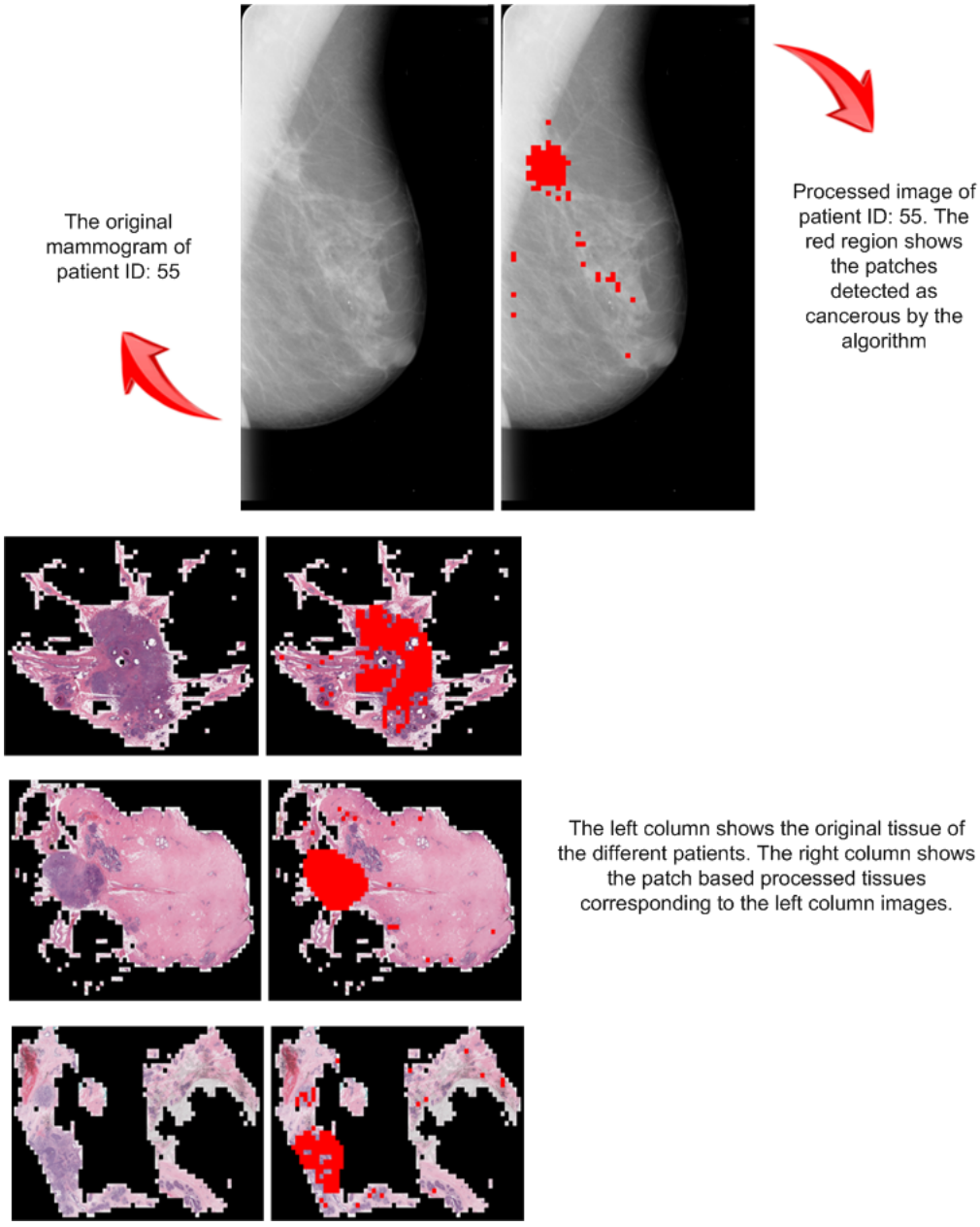

Figure 8: Analysis of mammogram-based and histopathological tissue-based cancer detection using patch-based attention mechanism.

The histopathological samples also contain diverse structural patterns, such as fat cells, connective tissues, and malignant cell clusters; the model analyzes patch by patch to distinguish between benign and malignant regions. Patch based processing rather than whole images is the dominant feature of the proposed method due to better localization, sensitivity, reducing false positives or false negatives, and a capability for layered attention processing. The model also avoids the problem of treating an entire image as containing cancer and instead targets specific parts to support patients in

identification, aiding healthcare decision-making in the clinic. Minor early malignancy may escape detection in full-image analysis if detected independently, but patch based approaches enable a fine-to-mid size malignancy to be detected in an optimal manner, leading to quick diagnosis.

The model does not identify overlapping of features in an image being used by partitioning features into different parts of the image. In both mammogram and histopathological pictures, the red areas in the image show regions in which attention is paid to a high level by the model. This is the area of the image where the AI identifies significantly cancerous tissue-related features. The color, pattern and quantity of these red patches can tell you something. Areas where there is a high probability, such as dense and clustered red areas would indicate malignancy. Small red patches everywhere could signal pre-cancerous changes or areas that need extra scanning. There are also few or no colored tissue areas in the non-cancerous patches confirming that the model can distinguish between healthy and cancerous tissues. And in applying a patch based approach with multiple layers of attention, the model is very accurate in detecting cancerous regions. This also gives strong confidence for malignancy detection, with red-highlighted areas in images processed by the model, that can achieve a precise cancer localization. This greatly facilitates the early and accurate BC diagnosis by enhancing patient outcomes by allowing for timely intervention.

Results were evaluated on 20% of patches randomly chosen from the final dataset using the final model. Testing results appear as a confusion matrix in **FIGURE 9**. The confusion matrix demonstrates the performance of the model.

The results of the model correctly identified 38,554 non-cancerous cases (true negatives) and 15,273 cancerous cases (true positives), indicating high general accuracy. However, 1,194 non-cancerous cases were classified as cancerous (false positives), and 484 cancerous cases as non-cancerous (false negatives). As this model has good accuracy (~97%) and good recall (~97%), it can identify cancerous cases effectively. A few false negatives will not create any risk as for most of the patches being detected as cancerous, the proposed model definitely will confirm the mammogram under test as cancerous (**FIGURE 9a**). A full set of patches derived from four patients were also subjected to testing using the model. The outcomes are represented in the same figure as confusion matrices. (**FIGURE 9b**) for Patient ID 0999; for cancerous patches, the model achieved 98.32% accuracy with 4,867 true negatives and no false positives, however 58 were missed. Patient ID 8863 (**FIGURE 9c**) showed slightly worse accuracy with 94.28%, mostly from 54 false positives but only missed 2 cancerous cases. The model outperformed for Patient ID 8867, showing 98.90% accuracy in this case, yielding 16 false positives and 2 false negatives (**FIGURE 9d**). Finally, Patient ID 8913 (**FIGURE 9e**) performed with 95.50% accuracy with 42 false positives and only 1 missed cancer. On the whole, the model consistently achieved a good value of accuracy on all test sets with a minimum of false negative data and significant importance was assigned to accuracy of the detection results to help to minimise the probability of missed clinical diagnoses. The comparison as shown in the **TABLE 1**, demonstrates that while recent studies predominantly focus on a single imaging modality or dataset, the proposed approach uniquely integrates mammographic and histopathological data with a circular attention mechanism. The multimodal and attention-driven design lead to improved diagnostic performance with higher accuracy and robustness, particularly in challenging imaging conditions. **TABLE 2**, shows the valuation metrics and performance values of the proposed model.

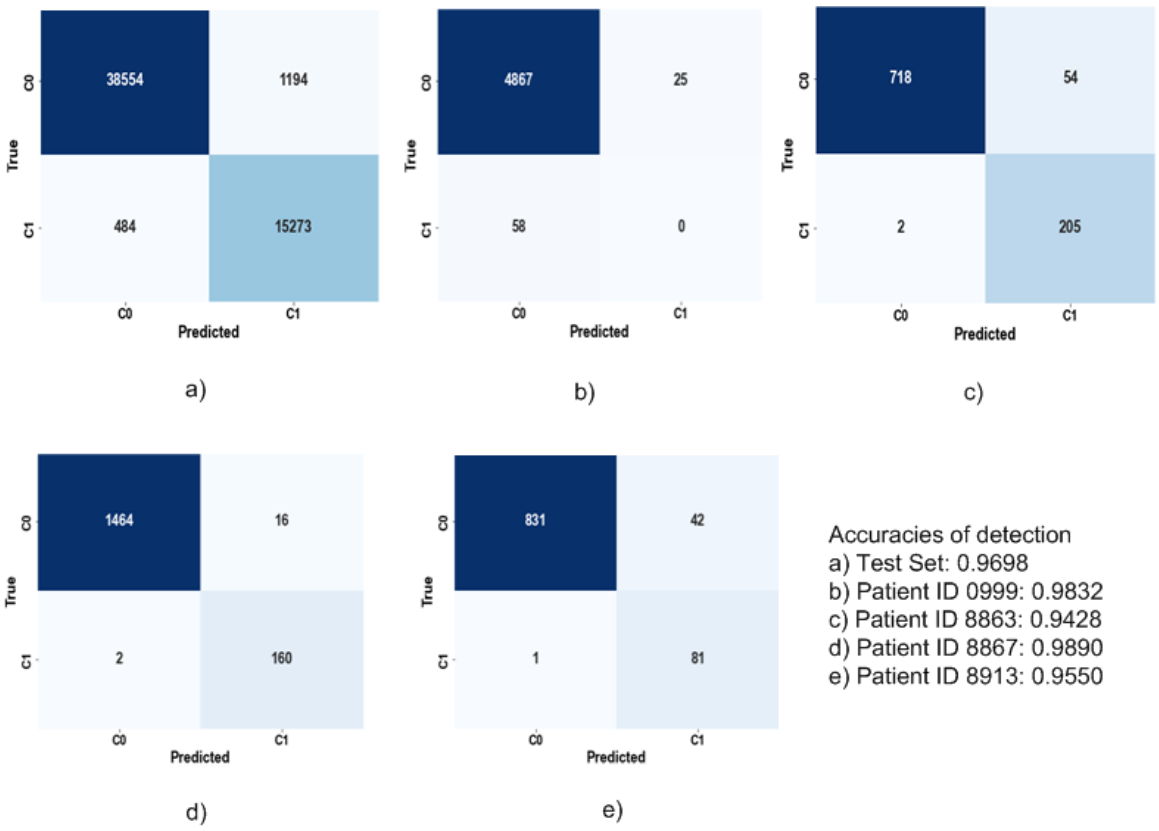

Figure 9: Confusion matrices for testing of the model using different test sets.

Table 1: Comparative analysis of recent research outcomes for mammographic breast cancer prediction.

Research	Dataset	Imaging Modality	Methodology
Shen et al. (2019) [37]	CBIS-DDSM	Mammogram	Deep CNN with attention mechanism
Ragab et al. (2020) [38]	CBIS-DDSM	Mammogram	Transfer learning–based CNN + SVM
Al-Antari et al. (2020) [39]	MIAS	Mammogram	Deep belief network–based CAD system
Yan et al. (2021) [40]	BreakHis	Histopathology	Hybrid deep CNN with multi-scale features
Campanella et al. (2019) [41]	CAMELYON16	Histopathology	Weakly supervised deep learning on WSIs

Table 2: Quantitative evaluation metrics and corresponding performance values achieved by the proposed model.

Accuracy	≈97.0%	Overall correctness of classification
Precision	≈92.8%	Reliability of cancer-positive predictions
Recall (Sensitivity)	≈96.9%	Ability to detect cancerous patches
F1-Score	≈94.8%	Balance between precision and recall
Specificity	≈97.0%	Ability to correctly identify non-cancerous patches

5. CONCLUSION AND FUTURE SCOPE

This study indicates that the utilization of CNNs integrated with attention systems may potentially improve the detection of breast cancer (BC) as seen in the present research. Patch-based detection in the proposed model would provide further localization of the more cancerous areas of interest, which can help refine diagnosing more efficient with higher precision of the malignancy. As shown in this study by dividing mammograms into separate 50×50 pixel patches, the model succeeds in identifying the cancerous structures that are not being detected in the whole image.

A circular attention mechanism enables better targeting of the diagnostically significant areas, improving both sensitivity and interpretability. The accuracy of the model was around 97% leading to reduced false positives and false negatives. Histopathological analysis is integrated to help in the diagnostic capability by assessing structures at the tissue level and ultimately helping the model to differentiate between benign and malignant patches.

Attention maps were also useful for understanding the model's focus and are used to ensure transparency in diagnostics. Strong generalization capability is supported by appropriate augmentation of the data and strong preprocessing. The attention mechanism should be further optimised in future works to mitigate the potential risk of false positives, as well as to increase the performance of the model to address complex mammogram patterns. Adding a more diverse and more widely scattered imaging conditions to the dataset would make the model more robust and flexible to the diversity. Moreover, the incorporation of multi-modal imaging data (the ultrasound and MRI) also has the potential to improve the model's diagnostic capabilities, which leads to increased breast cancer screening, early detection, and better end-to-end patient outcomes in real-world clinical environments.

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