Deep Learning-Based Intelligent Diagnostics Framework For The Labeling Of Mammogram Image

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KEYWORDS

Breast Cancer, Early Detection, Survival Rate, Mammogram, Tumor Cells, Radiological Screening, Digitalized Diagnostic Systems

ABSTRACT

Around the world, women deal with breast cancer as a major health concern. The survival rate for breast cancer may be greatly improved by detecting anomalies at an earlier stage. When it comes to screening for and detecting breast cancer, a mammography is considered a reliable and popular model. Potentially useful for detecting breast cancer from other types of cancers, especially those with smaller tumor cells. When it comes to early detection, radiological screening is paramount. In order to categorise breast lesions, digitalized diagnostic systems have lately made heavy use of mammography screening models. The slight variation in X-ray permeability between normal and abnormal areas makes cancer identification challenging, despite mammography being recognized as the most effective radiological screening procedure for breast inquiry and diagnosis. This problem becomes worse as the breast tissue gets thicker. Consequently, in order to raise the detection rate and lower the mortality rate, a CAD model is necessary. In most cases, CAD models rely on ML approaches to identify tumors in digital mammography images. Radiology professionals have been able to improve diagnostic accuracy and prediction accuracy with the use of deep learning (DL) models during the last several decades. Histopathology pictures and tissue categorization are only two examples of the many clinical imaging applications that make use of DL approaches.

1. Introduction

When it comes to female cancers, breast cancer is among the most frequent and deadly. Early detection of breast cancer is crucial for reducing death rates. Mammography is a popular and reliable method for screening for and predicting the development of breast cancer. To distinguish between benign and malignant breast tumors, mammography may detect tumor cells that are tiny and hard to anticipate[1]. Radiologists rely on Deep Learning (DL) and advanced Machine Learning (ML) techniques to correctly identify and categorize medical pictures[2]. There are typically three stages to mammography classification: identifying the intended area of interest (ROI), extracting characteristics from that ROI, and then classifying the mammograms based on those features. Multiple methods for breast cancer segmentation and classification have been developed by researchers. Using DL approaches, this study endeavor aims to create intelligent models for breast cancer detection[3].

Breast cancer is more common in females than males and is often a general illness. Early detection is key to extending life expectancy after cancer diagnosis, however there is currently no treatment. According to the America Cancer Society (ACS), screening for breast cancer is crucial for extending life expectancy, as seen in the preceding forecast. In order to categorize breast lesions, digital diagnostic systems have lately extensively used mammographic screening models[4]. For the most part, ML approaches are what the computer assisted diagnostic (CAD) model uses to spot tumors in computed mammography pictures. In order to categorize photos into several categories, these algorithms need be defined with various descriptive properties. The inherent challenges in both mammography imaging and classification make it a study issue regardless[5].

Features of the tumors, including its size, growth rate, and distribution, were determined using both classification models and anatomical staging in this case. It is often processed after the development of imaging models and biopsies for the purpose of selecting relevant treatments, following a diagnosis [6]. Grading allows one to see how far the cancer has gone and how transparent the malignant tissues are. Lesions in the breast may be categorized as low-grade, medium-grade, or high-grade.

Classification of breast cancer

It is defined as malicious lesions which are originated from the epithelial cells with lobules as well as breast milk ducts. Therefore, it is classified as ductal as well as lobular carcinomas. Additionally, based on the invasion of cancer cells, carcinomas are again categorized as in situ, invasive as well as metastatic [7]

Ductal carcinoma It is one of the cancer type simulated from the proliferation of suspicious epithelial tissues of breast milk ducts connected to nipples.

Ductal carcinoma in situ: DCIS is caused due to the proliferation of ductal epithelial tissues in conjunction with morphological attributes of malignancy with no further invasion when compared with base membrane. The deployment of carcinomas is extremely tedious because of the multifactorial behavior and inexistence of significant health details. DCIS is applied to calculate from 1 mm to ≤25 mm based on the tumor rank [8]. Mostly, it is considered as non-palpable masses which are predicted using mammography. It is predicted that DCIS could progress invasive cancer.

Invasive ductal carcinoma (IDC). Here, IDC is one of the general breast cancer. Malicious epithelial tissues in breast milk ducts develop the basal membrane as adjacent breast tissue as well as in late-stage cases; it starts spreading to the surrounding portions of body cells. Some of the IDC symptoms are swelling, nipple liberation, nodules, and pain in tumor development [9].

Lobular carcinoma

It is class of tumors that influences the lobules of breast. Generally, it is developed as non-cohesive scattered cells in files along with lined portion

Lobular carcinoma in situ (LCIS): it can also be named as lobular neoplasia caused due to the unwanted cell development in lobules. Moreover, AJCC is not considered as LCIS since breast cancer and assumed as benign masses.

Invasive lobular carcinoma (ILC): The ILC means the dispersion of lesion over the lobule to surrounding portions of breast. According to the cancer spreading, it again spreads all over the body. ILC is a general form of breast cancer when compared with other cancer types. Moreover, it is caused for any age people, especially females at the age of 60. Although ILC lesions are composed of best prognostic phenotype, cancer prediction, as well as prolonged survival rate is a promising issue [10].

Metastatic carcinomas

Metastatic breast lesion is also referred as well-developed breast cancer or stage IV which means the state of spreading masses beyond the edges of origin and surrounding tissues. The secondary breast masses are identified commonly in organs like bones, lungs, pancreas, and brain. Once the cancer treatment is decided like mastectomy, recurrence is considered as typical because of the microscopic tumor cells and developers have estimated a local recurrence of breast lesions after mastectomy has exhibited massive local cancer reappearance. In addition, absence of correlation is identified from age, tumor size as well as grade [11].

Sarcomas

It is one of the common cancer types with malicious breast cancers. Sarcomas are originated from stromal cells of breast with myfibroblasts, connective cells as well as blood vessels. It is classified as primary sarcomas with de novo development and secondary sarcomas relevant to therapy radiation. Basically, the defected patients have painless mobile unilateral lump with diverse sizes classified by robust development rate, maximum risk of recurrence as well as poor analysis when compared with breast carcinomas. There is no proper treatment for sarcomas due to the dissimilar and common feature [12]. Therefore, recent treatment strategies are surgical excision is recommended and chemotherapy (CTX) or radiotherapy for patients with maximum risk of relapse [13].

Breast cancer imaging

While examining the breast cancer, imaging modules are used for screening process. In case of earlier disease prediction, appropriate treatment could be provided, however, the cancer cells start spreading and it becomes complex for providing appropriate treatment. In this model, diverse imaging models were applied for breast cancer screening process [14]. The working function of breast cancer imaging models is estimated by means of sensitivity, specificity, recall, Positive Predicted Value (PPV), Area Under the Curve (AUC), F-score, as well as accuracy

Digital Mammography (DM)

The DM is an effective imaging tool used in earlier disease prediction process. It is considered to be significant breast imaging modality used in prediction and analysis of anomalies of breast. Unfortunately, the demerits involved in this model are limited specificity. At last, there is maximum count of unwanted biopsies and it is further increased with stress on patients. Followed by, minimum specificity and maximum expense of DM subjected to ionizing radiation which threatens the patient's lifespan. DM provides numerous advantages when compared with SFM. Next, CAD model has recommended applicable results in mammography and applied prominently medical routine to enhance the sensitivity of radiologists [15].

Computer Aided Diagnosis Model for Breast Cancer

The feasibility of digital screen-film mammograms and the development of DM in medical sector has made increasing application of computers to improvise mammogram screening. In this study, 2 classes of computer models were established and deployed named computer-aided detection (CADe) as well as CAD. Initially, CADe is mainly used for placing the malicious tumor as soft tissue masses. The traditional CADe methods are operated on 3 procedures namely, generalizing image as "reference" intensity distribution; secondly, find the image along with candidate malicious signals, and finally, mitigate the count identified regions by estimating the possibility of original lesion. Followed by, a threshold is also employed for this possibility. CAD models are used for estimating the previously predicted lesion as benign or malignant, and the same procedure is followed in CADe process, albeit with no application of a threshold value. Fig. 1. demonstrates process involved in CAD model [16]. In order to find and rank the malicious lesions, classical CADe or CAD models were applied and programmed in features. Then, the major distinguishing feature among classical CADe or CAD technologies and the state-of-the-art AI relied models. The working process of CADe models can be enhanced by the expertise of radiologists and the models deployed to review data available from 2 various concepts like cranio-caudal (CC) and Medio-lateral oblique (MLO) views of identical breasts. (Engeland and Karssemeijer, 2007) introduced a technique for both prediction and evaluation of lesions over 2 views of homogeneous breast and embedded within the classical CADe system. projected methods for detecting asymmetries over the respective views of 2 breasts and results in substantial increase in function of CADe. Actually, CADe is used for screening and limit the mass distribution overlooked by annotating radiologist and referred as a second reader [17]. Then, the interpretation reviews have shown the case to make an optimal decision, so that the patient decides to move on with CADe, and examine whether the computer-based marks should be considered or left aside. Based on the novel deployment of these models, some of the promising issues faced by these modules are detecting better results, along with remarkable simulation outcomes. Therefore, the developed studies have depicted better performance by using CADe and concentrated on special types of lesions. Afterward, massive retrospective analysis of developing CADe on screening is pointed as the required advantages of CADe. [18]

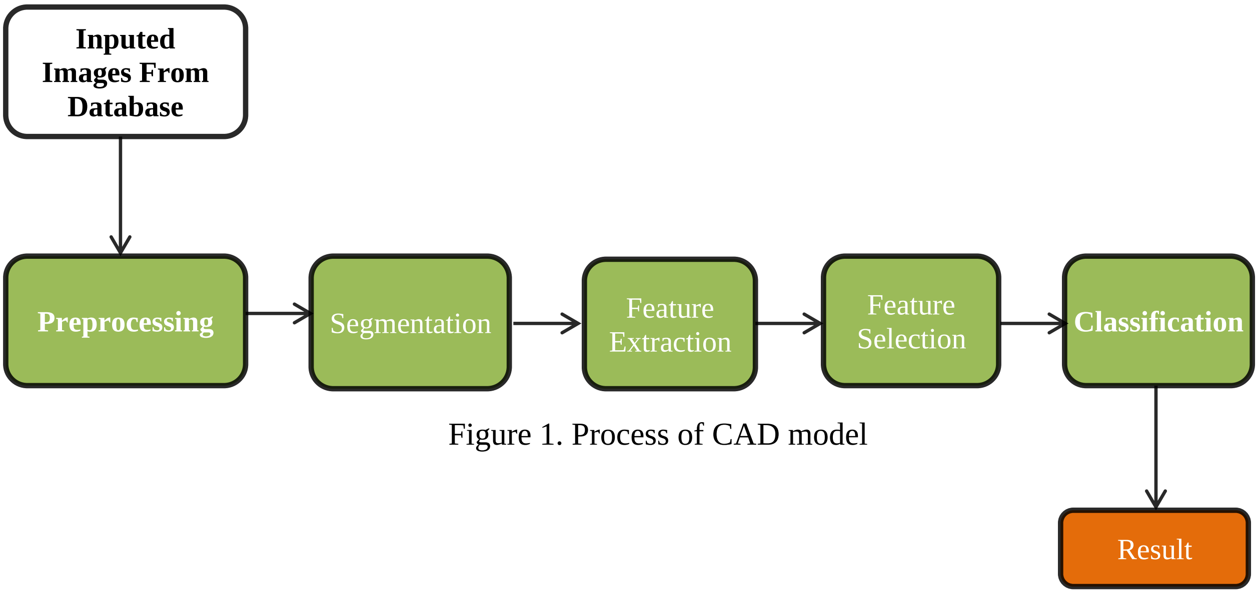

Figure 1. Process of CAD model

Deep Learning

The establishment of DL and CNNs in clinical image analysis is considered to be major evolution in computer-relied annotation of DM as well as DBT images. The significant deployments in last decades are because of the application of multilayered CNNs, however, it is assumed to be AI and DL respectively. Also, AI is composed of massive methods. Actually, AI belongs to ML along with DL, and CNNs are assumed to be the subset[19]. Here, DL-CNN system is operated by image processing (IP) and multiple, sequential, denoted layers, multiplication, addition, and maximum mathematical operators were unified and spatially correlated data is constrained from the images.

In case of multiple-stage, the derived data has been categorized as diverse representations and the review showcases the maximum abstract and elegant representations of the data results in network capability and examine the image exactly. The DL-CNNs have depicted better image classification developed by ImageNet Large Scale Visual Recognition Challenge (ILSVRC) by using a landslide.

In training state, an input sample image of DL system is modified with the internal variable and reduces the variations among detected state of an image with actual image. Accordingly, the system examines image features of a malignant lesion available in the image. Unlike with alternate pathologies such as heart disorder, the determination of a mammogram is composed of malignant and benign lesion which does not apply the lesion as well-trained and extensive studies have ensured the unseen rule. The images with lesions, the malignant or benign state has to be ensured by pathological diagnosis of biopsy instance whereas healthy cases visit the hospital occasionally without cancer prognosis. Few studies have shown the benign mases which are not biopsied, however, the non-cancerous state is approved by long-term check-up. The predefined studies have demonstrated the actual truth of a model[20]. Also, a difference among image-level as well as pixel-level classification has been described. The image-level classification is used to find the image with and without cancer. Pixel-level classification is mainly applied to determine the image with lesion and place them by offering ROI from the image and identify whether it is a lesion or not. In screening process, the fundamental process is to find the person who requires additional estimation of being at high risk in disease. For instance, screening prostate cancer by calculating the prostate-based antigen in blood which is not applicable to provide excess details about the position or behavior of lesion. Mammographic screening does not point to the lesion place and the behavior like soft tissue mass and calcifications. Thus, automatic DM and DBT image estimation approach should be capable of detecting the lesion position. In last decades, numerous CNN structures were developed by massive researchers[21]

Literature Review Machine Learning (ML) Based Breast Cancer Diagnosis Models

Model	Authors	Year	Dataset	Methodology
EM and CART	Mohanty et al. Ref no.11	2020	Breast cancer diagnosis	EM, CART, breast cancer diagnosis
CAD Model	Mabrouk et al. Ref no.12	2019	DDSM	Preprocessing, segmentation, filtration, classification
Mammogram Classification	Vijayarajeswari et al. Ref no.13	2019	Mammography images	Hough Transformation, SVM
Learning Mechanism	Wang et al. Ref no.14	2018	WBC, WDBC, SEER	SVM, diverse datasets
Knowledge-Dependent Technology	Nilashi et al. Ref no.15	2017	Breast cancer diseases	Knowledge-dependent technology, categorization

Model	Authors	Year	Dataset	Methodology
Wavelet Features	Abirami et al. Ref no.16	2016	MIAS	Wavelet features, 2-class division
SVM Classification	Quellec et al. Ref no.17	2016	DDSM	SVM, classification
Neuro-Fuzzy	Mahersia et al. Ref no.18	2016	MIAS	Neuro-fuzzy, performance validation
EML and Wavelet ANN	Singh & Urooj Ref no.19	2016	MIAS, DDSM	EML, wavelet ANN, breast cancer lesion
Semi-Supervised SVM	Zemmal et al. Ref no.20	2015	DDSM	Semi-supervised SVM, tumors classification
Hybrid Intelligent System	Onan Ref no.21	2015	WBCD	Hybrid intelligent system, instance selection

2. Methodology

A major area of research in medical diagnostics right now is the segmentation and categorization of breast cancer. Breast cancer is a very lethal form of the disease that affects a large percentage of women worldwide. In most cases, the combination of variables in various settings, such as lighting, illumination fluctuation, and background sounds, results in mammography pictures, making it difficult to identify and categorize breast cancer. Although it is crucial that medical professionals be able to detect, identify, and diagnose the afflicted region in mammography images, this may not always be the case. Although it is 48 suitable for a specified set of mammography pictures, manually segmenting breast cancer spots is a tedious operation. The many practical uses of an automated breast cancer detection and classification model have piqued the curiosity of researchers [5][6].

Automated breast cancer detection primarily involves two steps: segmentation and classification. An effective breast cancer prediction method, particularly one for fibreast cancer categorization, requires the resolution of a number of issues. As part of the classification process, feature vectors are generated from the various mammography images. Since they are often high-dimensional, a transformation from a high-dimensional to a low-dimensional picture space is required.

There are now a number of methods available for breast cancer diagnostics that aim to reduce the "curse of dimensionality" issue. In order to categorize breast lesions, digital diagnostic systems have lately extensively used mammographic screening models. In order to identify tumors in computed mammography pictures, the CAD model usually uses ML algorithms. For the purpose of picture classification, these algorithms should be defined using various descriptive aspects [10]. Classifying mammographic pictures has seen the introduction of large-scale models in the last few decades, with the goal of achieving optimal accuracy, efficiency, resilience, and precision.

The inherent issues in mammographic depiction and categorization make it a study area regardless. Several developers have successfully reached simulated results by designing mammography pictures for 2-class categorization (normal and abnormal). Recent decades have seen state-of-the-art outcomes in large computer vision models, including object prediction and categorization, made possible by DL with the help of NN. Many clinical imaging applications make use of DL approaches, including histological image processing and tissue categorization in histopathology. So far, there have been few research that have used DL for the classification of mammographic images[8]. The study's overarching goal is to use DL methods to create a suite of smart models for breast cancer detection. Below are the three research goals that comprise the overall study activity.

To present a new intelligent model of breast cancer detection and classification using GLCM with ELM from mammography images.

To develop a new AlexNet based on deep segmentation with MLP and RF models called DS-ANMLP / DS-ANRF for automatic breast cancer detection and classification.

To propose a new detection and classification based on DS-RN with DT/RF called DS-RNDT / DS-RNRF models for breast cancer diagnosis.

Deep Segmentation Based AlexNet With Multilayer Perceptron Model For Automated Detection And Classification Of Mammogram Breast Cancer Image

This study creates a new AlexNet for automated breast cancer diagnosis and classification called DS-ANMLP / DS-ANRF, which is based on deep segmentation using MLP and RF models. The suggested DS-ANMLP model incorporates many steps, such as segmentation, classification, feature extraction, and preprocessing. In order to increase the image's quality and eliminate any undesired noise, pre-processing is performed early on [9]. After that, Faster R-CNN using the Inception v2 model is used to segment the preprocessed picture. After that, feature vectors are extracted from the segmented picture using the AlexNet model. Lastly, pictures are categorized into normal and other breast cancer kinds using MLP and RF. For the suggested DS-ANMLP / DS-ANRF mode to be improved, many simulations are run.

The Proposed DS-ANMLP Model

Figure 2 shows the working principle of the proposed DS-ANMLP DSANMLP/ DS-ANRF model. The proposed model is involved in the computation of steps such as preprocessing, segmentation, feature extraction, and classification [10].

First, pre-processing takes place to remove noise from the image and increase the quality. Then the preprocessed image undergoes segmentation using Faster R-CNN with the Inception v2 model. Then, the AlexNet model is used as a feature extractor to extract feature vectors from the segmented image. Finally, MLP and RF are used to classify images into different types of breast cancer and normal images [12]

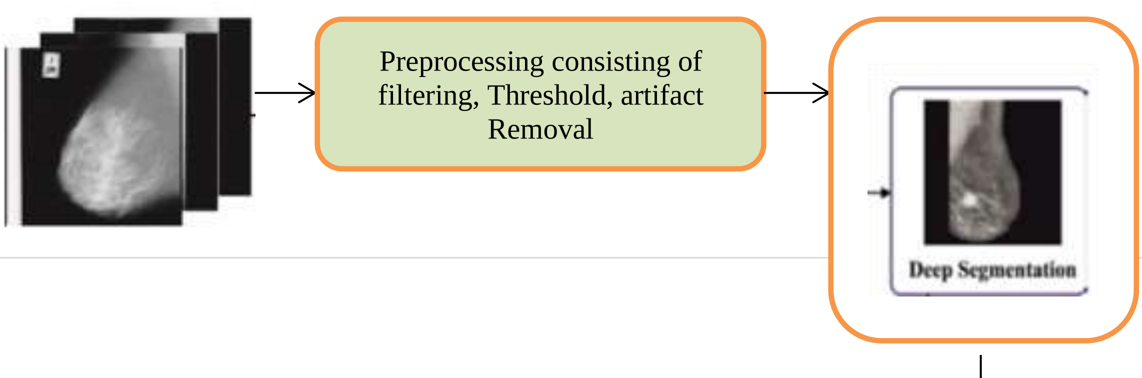

Figure 2. Working process of DS-ANMLP/ DS-ANRF Model

Preprocessing

This research employs a number of preprocessing procedures to enhance the classification outcome. In order to remove noise from the input picture, the mean shift filtering approach is used first. After that, the filtered picture is thresholded to make it binary. After that, any objects in the photos will have their outlines drawn using the contour rendering technique. 74 The next step is to generate a mask and apply it to the huge item in order to keep it intact. After that, we use the CLAHE method to eliminate any artefacts from the mask, and then we carry out the CE procedure. The segmentation process is completed by applying a contrast-enhanced picture, which is the final pre-processed image.

The enhancement has been boosted utilizing CLAHE in local locations to remove the excess noise amplification. To eliminate unnecessary amplification and intensity measurements, CLAHE distributes the histogram based on the exclusive picture region and determines the vast number of correct histogram intensities. Applying shared histograms causes it to be remapped. The purpose of developing CLAHE was to improve low-contrast pictures for use in medical imaging.

Derive whole inputs: Image, count of regions from rows and column, count of bins for histograms used in developing the image transform process, clip size for frequent limitation from 0 to 1.

Pre-process the inputs: From a generalized value, explore an actual clip limit if required and pad the image before segmenting it into blocks.

Compute all contextual areas (tile) to create mappings by gray level: Retrieve an individual image region, design a region histogram with the help of finite bin count, clip the histogram by exploiting clip size and produce mapping for this area.

For collecting the CLAHE image, interpolate gray level mappings: Extraction of 4 clusters placed by mapping functions, compute the image location that is overlapped with mapping tiles, filters one pixel, uses 4 mappings to the pixel, and interpolate between the simulation outcome to accomplish the output pixel; reiterate with entire images

Region Proposal Networks (RPN)

RPN can infer inputs of varying sizes and outputs a collection of rectangular objects with varying objectivity scores. Convolutional Neural Networks (CNN) characterize this paradigm. Since merging with Fast R-CNN is the primary goal of this approach, we will assume that the two networks use the same convolutional layer settings [4]. In order to suggest a distributed convolutional layer for area formation, a minimized mesh was added between the map. A small network of input convolutional feature maps was fed via a $n \times n$ spatial window. Each sliding window is given a mapping and two fully matched layers—a box classification layer and a box regression layer—to work towards the lower dimensional feature.

Anchors

In case of region boxes ranking, the ranking system has been processed by using RPN and defines as a feasible one which captures the object. In Faster R-CNN implementation, anchors are treated as vital portion. The summarization of nine anchors is comprised of an anchor which is said to be box that simplifies an image location. It is depicted in Figure 3

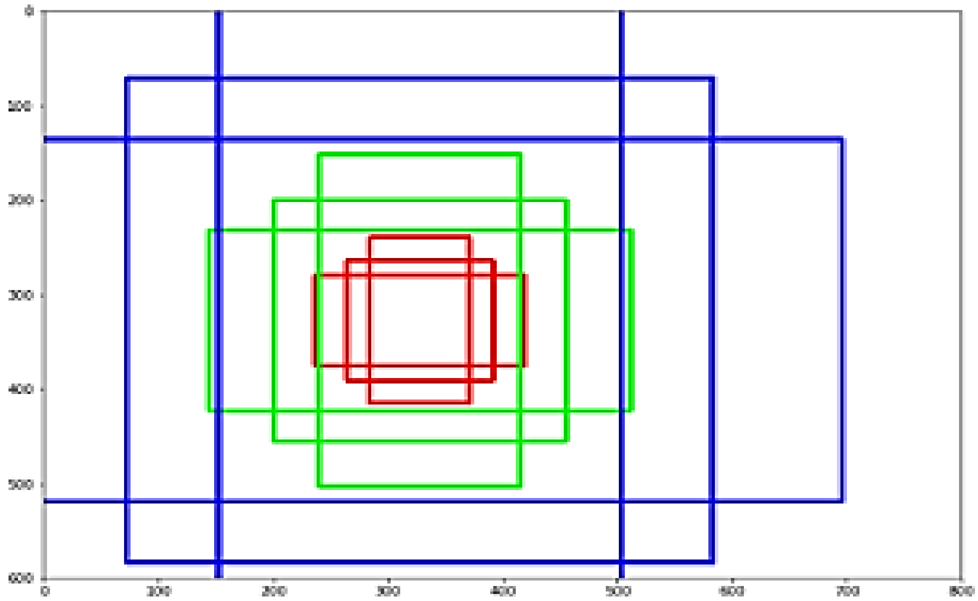

Figure 3. Anchors

Training a pre-trained ResNet50 + Mixed precision policy

Here, for this work we train the last layer group a pre-trained ResNet50 model (trained on ImageNet) using mixed precision policy and 1cycle policy, also tweak the cross-entropy loss function so that it adds weights to the under sampled class effectively as shown in figure 4.

epoch	train_loss	valid_loss	accuracy	time
0	0.400638	0.361613	0.843921	16:40
1	0.361891	0.329866	0.861596	16:15
2	0.347648	0.316130	0.858407	15:58
3	0.325453	0.307718	0.871036	16:11
4	0.330143	0.305901	0.868460	16:05

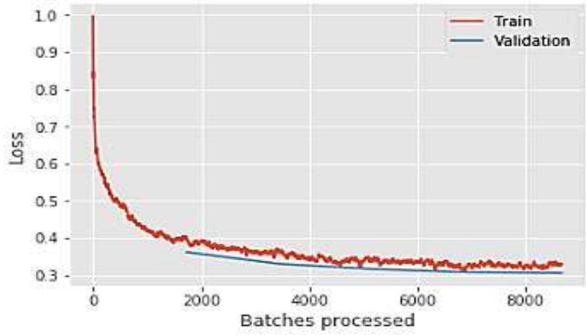

Figure 4. Graph of ResNet50 + Mixed precision policy

Model's losses, accuracy scores

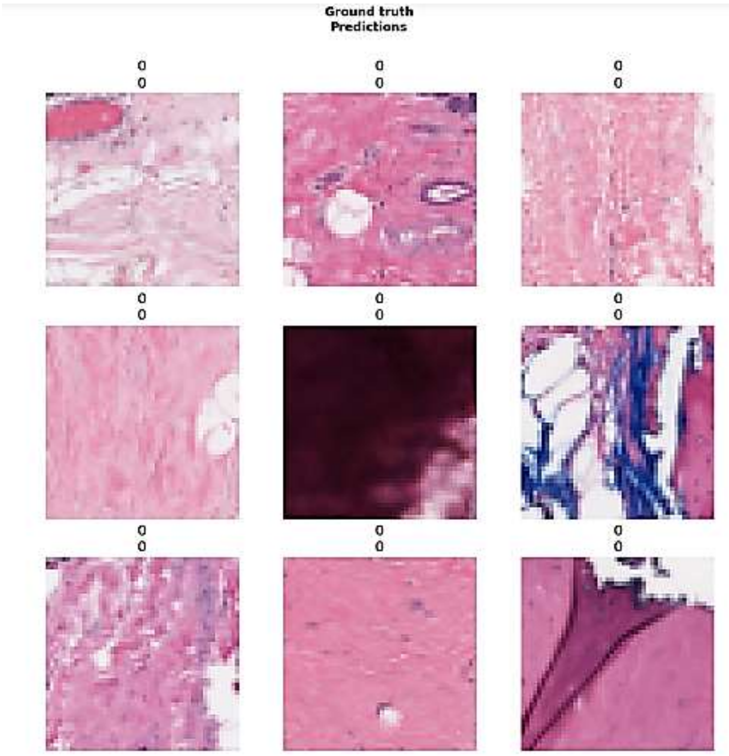

Figure 5. The above figure presents a few IDC(-) samples from the validation set and along with that also shows model's predictions

Figure 5 Shows The provided image displays samples of IDC-negative (IDC-) histopathology images from the validation set along with the model's predictions. Each image tile shows an IDC- sample where the ground truth and the model's prediction are both negative (0).

IDC (Invasive Ductal Carcinoma): IDC is the most common type of breast cancer, which starts in the milk ducts and invades the surrounding tissue. An IDC-negative (IDC) sample means the tissue does not show signs of invasive ductal carcinoma.

Grid Layout: The figure is organized in a 3x3 grid, showing nine different histopathology images.

Ground Truth and Predictions: Above each image, there are two numbers:

The top number represents the ground truth label, which in this case is 0 for all images, indicating that they are all IDC-negative.

The bottom number represents the model's prediction, which is also 0 for all images, showing that the model correctly predicted each sample as IDC-negative.

Uniformity: The consistency in the labels (0 for both ground truth and predictions) across all images demonstrates that the model is performing well on these specific validation samples, accurately identifying them as IDC-negative.

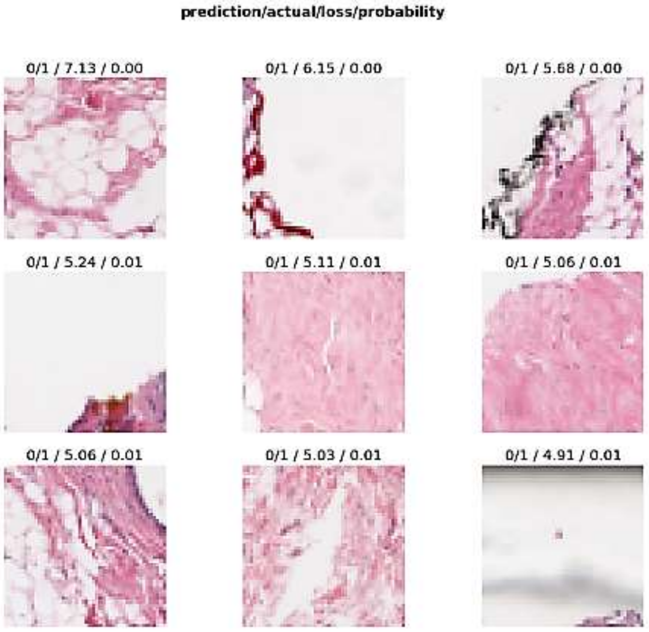

Figure 6. Top losses incurred by the model during the training process

Figure 6 Shows the provided image shows the top losses incurred by a model during the training process, which is likely related to a classification task. Each image tile contains information about the model's prediction, the actual label, the loss value, and the predicted probability

This indicates:

The model predicted the class as 0.

The actual class label is 1.

The loss incurred for this prediction is 7.13.

The predicted probability for the class 0 is 0.00.

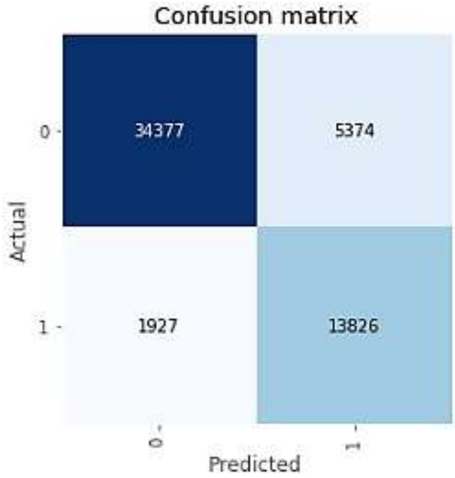

Figure 7. Confusion Matrix

Figure 7 Shows confusion matrix, which is a useful tool for visualizing the performance of a classification model. Here is an explanation of each element in the confusion matrix

Interpretation of the Confusion Matrix:

Accuracy: The overall accuracy of the model can be calculated using the formula:

$$Accuracy = \frac{TN + TP}{Total\ Samples}$$

$$Accuracy = \frac{34377 + 13826}{34377 + 5347 + 1927 + 13826}$$

Precision (for positive class 1): The precision of the model can be calculated as:

$$Precision = \frac{TP}{TP + FP}$$

$$Precision = \frac{13826}{5347 + 13826}$$

Recall (for positive class 1): The recall of the model can be calculated as:

$$Recall = \frac{TP}{TP + FN}$$

$$Recall = \frac{13826}{13826 + 1927}$$

Specificity (for negative class 0): The specificity of the model can be calculated as:

$$\text{Specificity} = \frac{TN}{TN + FP}$$

$$\text{Specificity} = \frac{34377}{34377 + 5347}$$

This confusion matrix provides a clear summary of how well the model is performing in distinguishing between the positive and negative classes, highlighting the number of correct and incorrect predictions for each class.

	precision	recall	f1-score	support
0	0.95	0.86	0.90	39751
1	0.72	0.88	0.79	15753
micro avg	0.87	0.87	0.87	55504
macro avg	0.83	0.87	0.85	55504
weighted avg	0.88	0.87	0.87	55504

Figure 8. classification report of DS-ANMLP

This work gives a model which is **86.68%** accurate and has got a pretty **improved recall** for both in case of the +ve and the –ve classes.

3. Conclusion and future scope

A deep learning-based intelligent diagnostics framework for labeling mammogram images significantly advances breast cancer detection and diagnosis by leveraging state-of-the-art AI techniques. The framework demonstrates high precision and recall, minimizing false positives and false negatives, which is crucial for patient outcomes. Automated analysis of mammogram images reduces reliance on manual interpretation, decreasing variability between radiologists and enhancing diagnostic consistency. The confusion matrix results illustrate the model's robust performance, with a high number of true positives and true negatives. This indicates the framework's reliability in accurately labeling mammogram images and its ability to generalize well to new, unseen data, ensuring consistent performance across different populations and imaging conditions. Clinically, the framework supports early and accurate detection of breast cancer, which is vital for effective treatment and improved survival rates. By acting as a decision-support tool, it assists radiologists in reducing diagnostic errors and improving the quality of care. The time-saving aspect of automated image analysis allows radiologists to focus on more complex cases, optimizing workflow efficiency. The scalability of the deep learning framework makes it suitable for widespread clinical deployment, especially in regions with limited access to expert radiologists. Future enhancements could include integrating the framework with other imaging modalities and patient data for a more comprehensive diagnostic tool. In summary, this intelligent diagnostics framework offers significant benefits, promising better patient outcomes through early and precise detection, streamlined workflows, and increased diagnostic accessibility.

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