Breast Cancer Detection Using Image Processing and Machine Learning

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Abstract*—Different breast cancer detection systems have been developed to help clinicians analyze screening mammograms. Breast cancer has been increasing gradually so scientists work to develop new methods to reduce the risks of this life-threatening disease. Convolutional Neural Networks (CNNs) have shown much promise In the field of medical imaging because of recent developments in deep learning. However, CNN's based methods have been restricted due to the small size of the few public breast cancer datasets. This research has developed a new framework and introduced it to detect breast cancer. This framework utilizes Convolutional Neural Networks (CNNs) and image processing to achieve its goal because CNNs have been an important success in image recognition, reaching human performance. An efficient and fast CNN pre-trained object detector called RetinaNet has been used in this research. RetinaNet is an uncomplicated one-stage object detector. A two-stage transfer learning has been used with the selected detector to improve the performance. RetinaNet model is initially trained with a general-purpose dataset called COCO dataset. The transfer learning is then used to apply the RetinaNet model to another dataset of mammograms called the CBIS-DDSM dataset. Finally, the second transfer learning is used to test the RetinaNet model onto a small dataset of mammograms called the INbreast dataset. The results of the proposed two-stage transfer learning (RetinaNet → CBIS-DDSM → INbreast) are better than the other state-of-the-art methods on the public INbreast dataset. Furthermore, the True Positive Rate (TPR) is 0.99 ± 0.02 at 1.67 False Positives per Image (FPPI), which is better than the one-stage transfer learning with a TPR of 0.94 ± 0.02 at 1.67 FPPI.

***Keywords*—breast cancer, image processing, machine learning, convolutional neural networks**

I. Introduction

The most common cause of death in developed countries such as China is cancer. There are 9.9 million cancer-related deaths and 19.3 million new cases in 2020 [1]. With an estimated (11.7%) of new cases, female breast cancer has exceeded lung cancer as the most widespread cancer. Stomach (5.6%), prostate (7.3%), colorectal (10%) and lung (11.4%) are the percentages of other cancers [1].

The chance of occurrence of breast cancer is increased by several factors, i.e., smoking, use of alcohol, reproductive factor, hormonal factor, and family history. Consequently, early-stage detection of breast cancer is a hot research area.

CNNs are deep feed-forward networks that are capable of achieving impressive results in many applications [2]. They can be used in medical applications effectively. However, the breast datasets are relatively small and are not enough to train CNNs. Consequently, there is a need for additional research to enhance the precision of cancer detection [3]. The enhancement can be achieved by using transfer learning and pre-trained models called RetinaNet. For the COCO challenge's object detection task, RetinaNet should classify objects into 80 classes [4]. However, RetinaNet must classify objects into two binary classes of mass and non-mass for the breast cancer detection task. The parameter that specifies the number of classes must be adjusted as a result. Appropriate learning rate, focusing parameter γ and weighting factor α should also be chosen carefully.

Society is significantly benefited from the early detection of breast cancer. People with breast cancer and their family can obtain timely medical recommendations, therapies, and support when the cancer is diagnosed early. The risk of death due to breast cancer can also be reduced if it is detected in the early stage [5]. This research will make the diagnosis of breast cancer faster and more accurate and improves cancer outcomes by allowing providing care at the earliest possible stage.

The main contributions that distinguish this research are highlighted as follows: First, a new framework for detecting breast cancer has been developed and is based on the RetinaNet model which is a cutting-edge, simple, one-stage object detector and uses a convolution neural network. Although RetinaNet has demonstrated its ability

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to perform common object detection tasks, it has not been fully evaluated to detect masses in mammograms. Second, a two-stage transfer learning has been used with the RetinaNet detector so the performance has been improved and better results have been achieved compared with the one-stage transfer learning methods. Third, the proposed framework is comprehensively evaluated using one-stage and two-stage transfer learning using CBIS-DDSM and INbreast datasets. Fig. 1 provides a more formal explanation of our research (hypothesis, the main objective, methodology, and result).

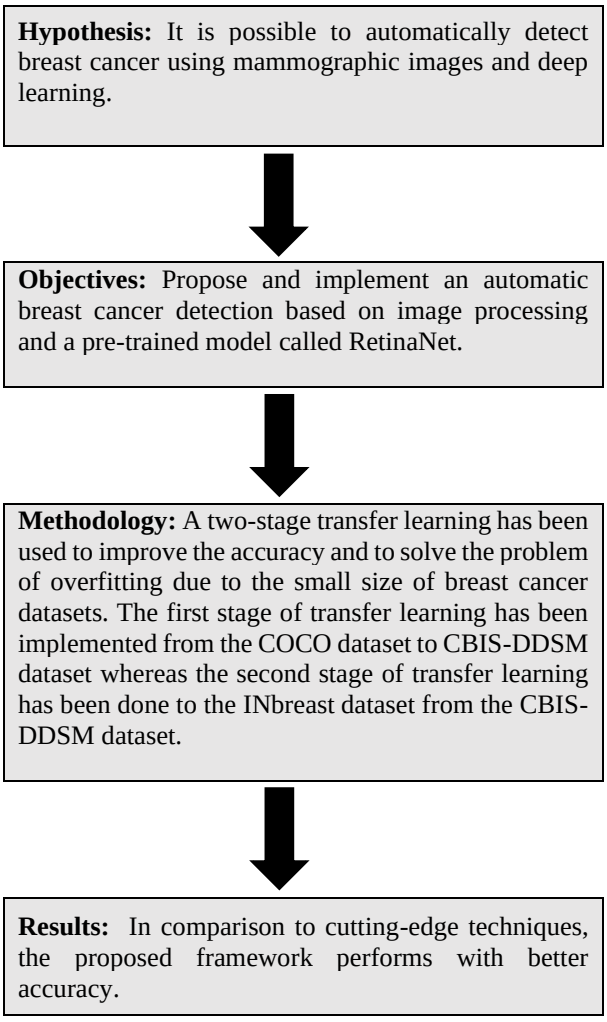


Figure 1. Hypothesis, main objective, methodology, and result.

The rest of the paper is organized as follows: the details about previous research on detecting breast cancer are presented in Section II. The details about the datasets and CNN architectures that have been used are included in Section III. This section also describes the instructions regarding transfer learning and how to train and test CNN models for mass classification and detection. The details of the experiments carried out in this research are described in Section IV. Finally, Section V presents the conclusions and recommendations.

II. Literature Review

In the past decades, breast cancer has been detected using a variety of Computer-Aided Diagnosis (CAD) methods. The non-deep learning-based systems have used image filters and utilized conventional machine learning models which rely on hand-engineered features [6–8]. However, meaningful features are difficult to define on mammograms due to changes in tissue context, texture, contrast, brightness, and density. In challenging situations, these systems demonstrated only limited accuracy [9].

The deep learning-based breast cancer detection systems can automatically identify which image features are most useful for making diagnoses, which improves the efficiency of these systems. Although several researchers have considered using deep learning to detect masses, breast cancer detection research has been restricted because there are few and small public breast cancer datasets [10]. Some researchers have been used transfer learning to overcome the small breast cancer datasets [10–12].

The authors of [13] proposed a new method for detecting breast cancer using the fusion of MRI and CT pictures with Fisher's Linear Discriminant Analysis (FLDA). A combination of techniques has been used in the proposed methods: filters for preprocessing pictures, and pixel normalization for CT and MRI images using histogram equalization; FLDA analysis has been used to select features from corresponding CT and MRI images. The MRI and CT images of each case are fused using FLDA.

Angulo *et al.* [14] audit CAD systems that can be used to mark suspicious parts in mammographic images which can help physicians detect breast cancer. The authors have emerged modalities like Digital Breast Tomosynthesis (DBT) for improving lesion characterization and tissue overlapping. Different cases were assessed and evaluated using the DBT-based method.

Agarwal *et al.* [10] Propose patch-based Convolutional Neural Networks (CNNs) to detect breast cancer. CBIS-DDSM dataset has been used in the training. The trained model is then transferred and tested using the INbreast dataset. VGG16, ResNet50, and InceptionV3 are tested and evaluated in this research because they are widely used pre-trained CNNs. The authors conclude that the InceptionV3 model has a better result than the other.

Lundervol *et al.* [15] have been focused on how to utilize deep learning in MRI. The latest advances and challenges of utilizing machine learning in medical image analysis and processing have been overviewed. The authors indicate how to utilize deep learning in MRI processing e.g. Image acquisition, image retrieval, image segmentation, and disease prediction.

Jung *et al.* [9] propose the pre-trained RetinaNet for cancer detection. A deep CNN has been used to create the RetinaNet. It is a fast and efficient one-stage object detector. However, RetinaNet has not been tested and evaluated to detect cancers in mammograms. Two datasets, the public dataset INbreast and the in-house dataset GURO have been used to test their method. The proposed detector

outperforms the more complicated two-stage detectors, according to the results.

In [16], the current molecular understanding of the MD is presented in this review. The association between its demography and the MD has also been reviewed. This review presents how to modulate MD using environmental factors. The law governing the detection of MD on a conventionally screened mammography has also been investigated.

Two research gaps can be identified; first, the convolutional breast cancer systems rely on hand-engineered features extraction which is difficult to define on mammograms due to changes in tissue context, texture, contrast, brightness, and density. Second, the deep learning based breast cancer systems suffers from overfitting due to the small size of breast cancer datasets.

III. Methodology

In this section, the datasets that have been used to train and test the proposed framework have been described, and the architectures of the CNN have been presented. Finally, the proposed framework used for breast cancer detection has been introduced. Fig. 2 shows the block diagram of the proposed framework.

A. Datasets

Three datasets have been used to train, validate and test the proposed method:

- COCO dataset

The Common Objects in Context (COCO) dataset [17] in machine learning is a popular object recognition dataset. It contains hundreds of thousands of images that can be used for computer vision. It contains 330 K images and more than 200 K labeled. It contains 91 stuff categories and 80 object categories. It includes 330,000 images and 5 captions per image.

- CBIS-DDSM dataset

The DDSM [18] is a public mammographic image dataset. It creates from scanned and compressed mammography films. They use lossless JPEG encoding for compression. This research uses the CBIS-DDSM dataset, a modern version of the DDSM dataset [19]. A DICOM format has been used in the new version. It contains 3061 images of 1597 cases.

The CBIS-DDSM dataset contains breast and non-breast areas. Therefore, a segmentation stage is required to extract the breast area. The dataset is split into a training set and a testing set. 1231 images for training and 361 images for testing. Moreover, 985 images from the training set have been used for training and 246 images have been used for validation.

- INbreast dataset

This dataset includes 410 DICOM-formatted digital mammograms [20]. It contains 410 images acquired from 115 cases. In this research, to separate the breast area from the background in images, a global threshold is used. The dataset contains histological information and pixel-wise annotations about the type of cancer.

B. Artificial Neural Networks (ANNs)

ANNs are motivated by the biological neural networks found in animal brains. ANNs were introduced in the 1950s [21].

A hidden layer, an output layer, and an input layer make up the ANN. Nodes known as (artificial) neurons make up every layer. The connections among nodes are called edges. A numerical parameter called weight is associated with each input to transform its value within the network's layers.

ANNs are not suitable for image processing because of the unmanageable weights in large images and overfitting can occur in the training stage. Furthermore, the loss of spatial information of input image. The CNNs can be used instead of ANNs with image processing.

In the Machine learning field, CNNs are one of the best options for image recognition, image classifications, object detection, face recognition faces, etc. [9]. CNNs consist of several convolutional layers.

The output value of each pixel is determined by applying a filter using a convolution operation.

C. Model Description (RetinaNet)

One-stage object detection is provided by RetinaNet [4]. Fig. 2 shows the architecture of the RetinaNet. It was presented in 2017 by Facebook AI Research (FAIR) team. It works well with small-scale and dense objects. The class imbalance has been identified as the main problem with one-stage detectors [9]. Two improvements have been added to RetinaNet to achieve better performance than existing one-stage object detection models in terms of running time and accuracy: Focal Loss [4]and Feature Pyramid Networks (FPN) [22].

Focal Loss (FL) is a novel loss function that is simple but effective. FL is introduced with one-stage object detection models to handle the class imbalance problem. One-stage detectors suffer from the problem of a huge number of sampling of anchor boxes [4]. A few anchor boxes are assigned by the RetinaNet model to solve the problem.

In computer vision, image pyramids provide an efficient representation for space scale invariant. This makes the pyramid scale invariant. Image pyramids subsample each image into lower resolution and smaller size images. The subsampled images are then used to extract different features [22]. Image pyramids are computing and memory intensive.

CNNs can be used instead of image pyramids. The pyramid itself can be obtained from the structure of the CNNs. The pyramidal structure is formed by the CNNs because the size of feature maps decreases due to convolutional operations. Fig. 3(a–d) shows the network architecture of RetinaNet.

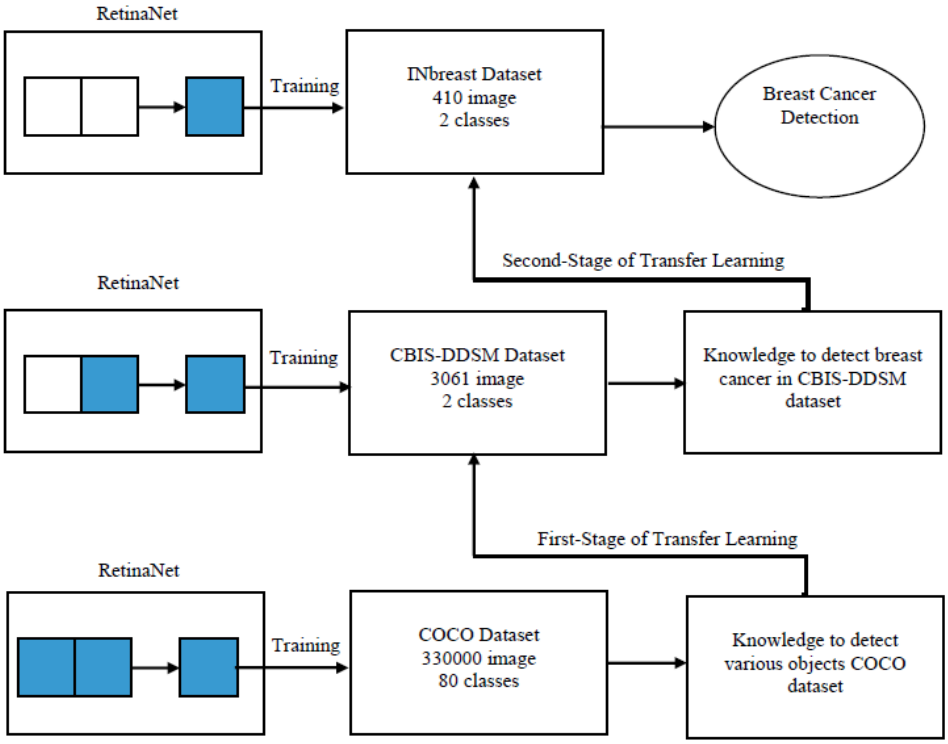


Figure 2. The block diagram of the proposed breast cancer detection system. The blue boxes in the RetinaNet model represent the training parts while white boxes represent the freezing parts.

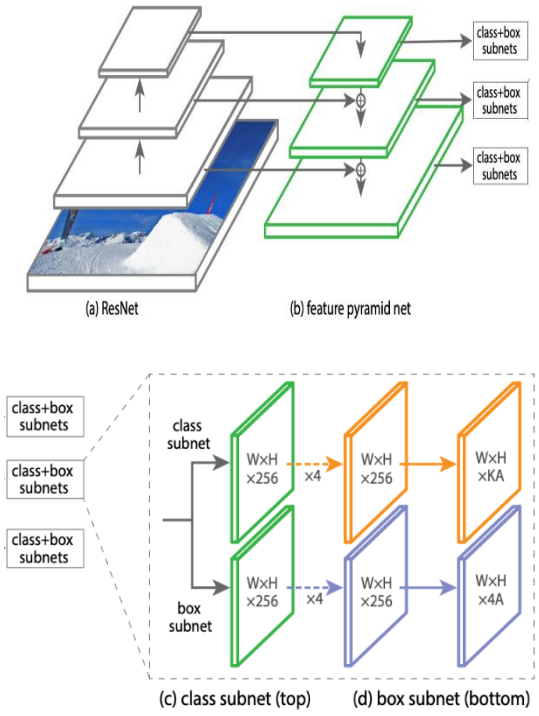


Figure 3. The network architecture of RetinaNet [4].

A backbone network and two subnetworks make up RetinaNet. The output of the backbone is subjected to convolutional bounding box regression and convolutional object classification by the subnetworks.

Feature Pyramid Network Backbone: It is built on top of ResNet101 or ResNet50 [23]. Other classifiers can also be selected when designing the network. It generates different sizes of the feature.

Anchors: Translation-invariant anchor boxes are used [22]. Three anchors of sizes {22/3, 21/3, 21/3} are added to each original three anchors**.** In total nine anchors have been used at each pyramid level.

Classification Subnet: It is used to predict the probability of detecting an object at each spatial location [4]. Each pyramid level is attached to the classification subnet. Objects can be detected at a different scale at each level of the pyramid [9].

Box Regression Subnet: The offset from each anchor box to an adjacent main object is regressed by this subnet to the object classification subnet. Every level of the pyramid has a box regression subnet connected [4].

Focal Loss: Cross-entropy loss function (CE) is improved by using a modulation term called focal loss. It handles the class imbalance problem. Eq. (1) represents the Focal Loss function:

$$FL(p_t) = -\alpha_t(1-p_t)^{\gamma}\log(p_t) \quad (1)$$

where γ is a parameter used to regulate the modulating term's strength, the weight α is assigned to the minority class.

D. Transfer Training

In machine learning, It enables a model that has been trained on big image datasets to be applied to new tasks [12]. Training the CNN model using an insufficient dataset may lead to low performance. Therefore, sufficient datasets that are collected for a similar task can be used by researchers and then transfer learning to the insufficient

datasets [9]. The researchers can also use publicly available pre-trained CNN models to apply them to other datasets.

In this research, we introduce a two-stage transfer learning of the RetinaNet model which is pre-trained using the COCO dataset. The proposed cascade of transfer learning is as below:

- **RetinaNet → CBIS-DDSM → INbreast**

The architecture of the CNN models consists of two parts: convolutional base and classifier [24]. The convolutional base is used for features extraction while the classifier is used for image classification. Hierarchical feature representations can be automatically learned by the CNN model [25]. As a result, the features of the last layers are specialized and dependent on the dataset and task selected, whereas the features of the first layers are general and may apply to different problem domains. In other words, the classifier component and part of the top layers of the convolutional base of CNN models correspond to specialized features, whereas the lower layers of the convolutional base, those closest to the inputs, refer to general features. Three strategies can be used for transfer learning: train the entire model, train only the classifier part, or train the classifier and part of the convolutional base [24]. Fig. 4 shows the architecture of the CNN models.

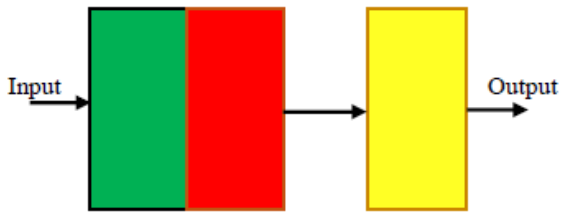


Figure 4. The parts of pre-trained models. The yellow part represents the classifier, and the green and red parts represent the base of features extraction.

- First Stage Transfer Learning

The pre-trained RetinaNet is originally trained with the COCO dataset. This dataset contains hundreds of thousands of images so the model is capable to classify between 80 objects efficiently. As a consequence, it can be used as a base for transfer learning to significantly smaller mammographic image datasets. This circumstance will motivate us to go to the first stage of transfer learning. Two components of the RetianaNet model will be trained with the CBIS-DDSM dataset: the classifier and the top layers of the convolutional base.

- Second Stage Transfer Learning

The pre-trained model with the CBIS-DDSM dataset that is produced by the first stage of transfer learning will be used with the INbreast dataset. The CBIS-DDSM is a good size dataset that contains sufficient lesion cases. It is also very similar to the INbreast dataset and only the mode of acquisition is different. The classifier of the RetinaNet Model will only be trained in the second stage of transfer learning.

IV. Experimental Results

The performance of the proposed framework has been analyzed using three metrics: the TPR, FPPI and the FROC curve. The FROC curve is a method for simultaneously assessing a free-response framewok's performance at all decision thresholds [26]. It shows the relationship between the TPR and the FPPI. The TPR equation is given by:

$$TPR = \frac{TP}{TP+FN} \tag{2}$$

where *FN* is the number of false negatives and *TP* is the number of true positives. The FPPI equation is given by:

$$FPPI = \frac{FP}{Number\ of\ tested\ frames} \tag{3}$$

where *FP* is the number of false positives. The number of classes of the breast cancer detection task is 2 (mass and non-mass) whereas it equals 80 classes for the COCO dataset's object detection task. As a result, the subnet's parameter K in the RetinaNet model, which specifies the number of classes, is set to 2 instead of 80. The best values that were proved in the original article about the RetinaNet model are used [4, 9], which were set to 0.25 for the weighting factor (α), 2 for the focusing parameter (γ) and 0.00001 for the learning rate. The training and testing sets of the INbreast and CBIS-DDSM datasets have been chosen to be similar to [27], which means half of each dataset's images are utilized for training, and the other half is used for testing.

Table I shows the performance of the RetinaNet model using a one-stage transfer learning (RetinaNet → INbreast), where the (μ ± σ) refers to the mean plus/minus the standard deviation. The higher TPR is **0.94** at **1.67** FPPI. Table II shows the performance RetinaNet model using a two-stage Transfer Learning (RetinaNet → CBIS-DDSM → INbreast). The higher TPR is **0.99** at **1.67** FPPI. Consequently, the proposed two-stage Transfer Learning achieves better performance compared with the one-stage transfer learning. Table III pressents a performance comparison of the previous methods and the proposed framework. Fig. 4 shows the FROC curve on INbreast using one-stage learning transfer learning and two-stage learning transfer.

The intermediate results using the CBIS-DDSM dataset are shown in Table IV. The accuracy is less than the accuracy of the proposed two-stage transfer learning due to the dissimilarity of the COCO and CBIS-DDSM datasets. However, this transfer learning is significantly useful because it can be used as a base for the second transfer learning.

The results of the proposed framework with small and large mass sizes have been shown in Table V. The lesions in the INbreast dataset have been divided into two categories: the size of small lesions is smaller than 2 cm while larger lesions are equal to or greater than 2 cm. The TPR of the proposed framework with small lesions is 0.93 at 0.5 FPPI, while the TPR with large lesions is 0.98 at 0.5 FPPI.

TABLE I. THE PERFORMANCE OF THE RETINANET MODEL USING A ONE-STAGE TRANSFER LEARNING

Model	Pretrained dataset	Fine tune	FPPI	TPR (μ ± σ)	Training cascade
RetinaNet	COCO	YES	0.25	0.89 ± 0.07	RetinaNet → INbreast
RetinaNet	COCO	YES	0.44	0.90 ± 0.06	RetinaNet → INbreast
RetinaNet	COCO	YES	0.58	0.91 ± 0.05	RetinaNet → INbreast
RetinaNet	COCO	YES	0.79	0.93 ± 0.03	RetinaNet → INbreast
RetinaNet	COCO	YES	1.67	0.94 ± 0.02	RetinaNet → INbreast

TABLE II. THE PERFORMANCE OF THE RETINANET MODEL USING A TWO-STAGE TRANSFER LEARNING

Model	Pretrained dataset	Fine tune	FPPI	TPR (μ ± σ)	Training cascade
RetinaNet	CBIS-DDSM	YES	0.25	0.90 ± 0.06	RetinaNet → CBIS-DDSM → INbreast
RetinaNet	CBIS-DDSM	YES	0.44	0.93 ± 0.05	RetinaNet → CBIS-DDSM → INbreast
RetinaNet	CBIS-DDSM	YES	0.58	0.94 ± 0.04	RetinaNet → CBIS-DDSM → INbreast
RetinaNet	CBIS-DDSM	YES	0.79	0.96 ± 0.04	RetinaNet → CBIS-DDSM → INbreast
RetinaNet	CBIS-DDSM	YES	1.67	0.99 ± 0.02	RetinaNet → CBIS-DDSM → INbreast

TABLE III. A COMPARISON OF THE PROPOSED FRAMEWORK AND PREVIOUSLY PUBLISHED METHODS

Paper	TPR (μ ± σ) @FPPI	Method
Ours	0.90 ± 0.06@ 0.25 0.93 ± 0.05@0.44 0.94 ± 0.04@0.58 0.96 ± 0.04@0.79 0.99 ± 0.02@1.67	Deep Learning (Two-stage Transfer Learning)
Ribli *et al.* [28]	0.90 @ 0.3	Deep Learning
Kozegar *et al.* [29]	0.87 @3.67	Ensemble Classifier
Dhungel *et al.* [11]	0.95 ± 0.02@5 0.90 ± 0.02 @ 1.3	Deep Learning
Akselrod-Ballin *et al.* [30]	0.93 @ 0.56	Deep Learning
Agarwal *et al.* [10]	0.98 ± 0.02 at 1.67	Deep Learning

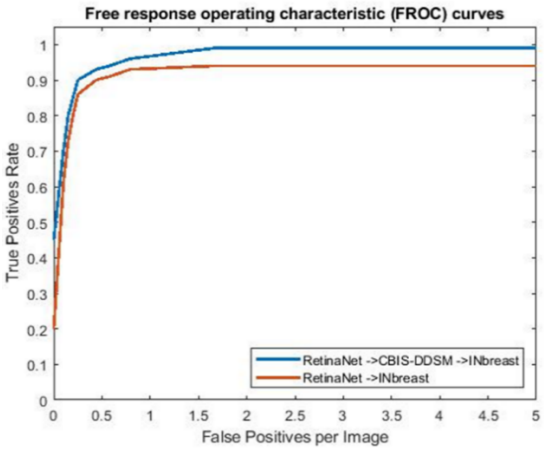


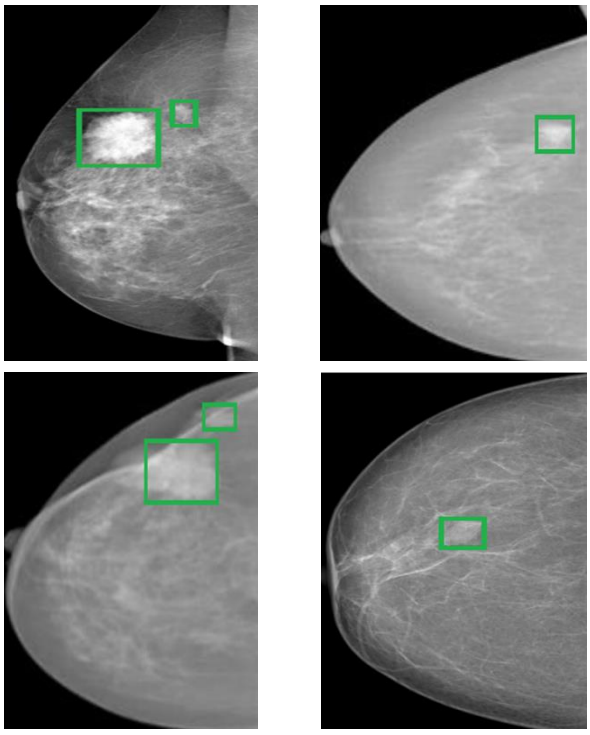
Figure 4. The FROC curve of One-stage learning transfer & Two-stage learning transfer (INbreast dataset).

TABLE IV. THE INTERMEDIATE PERFORMANCE OF THE RETINANET MODEL WITH THE CBIS-DDSM DATASET

Model	Pretrained Dataset	Fine Tune	FPPI	TPR (M ± Σ)
RetinaNet	COCO	YES	0.25	0.90 ± 0.06
RetinaNet	COCO	YES	0.44	0.91 ± 0.05
RetinaNet	COCO	YES	0.58	0.92 ± 0.04
RetinaNet	COCO	YES	0.79	0.91 ± 0.04
RetinaNet	COCO	YES	1.67	0.94 ± 0.03

TABLE V. THE PERFORMANCE OF THE PROPOSED FRAMEWORK WITH SMALL AND LARGE MASS SIZES (INBREAST DATASET)

Lesion Size	Fine Tune	FPPI	TPR	Training Cascade
small	YES	0.5	0.93	RetinaNet → CBIS-DDSM → INbreast
large	YES	0.5	0.98	RetinaNet → CBIS-DDSM → INbreast



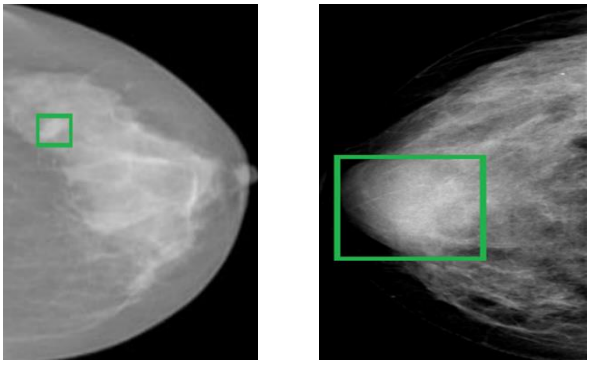


Figure 5. The results of the proposed framework of six samples in the INbreast dataset.

Fig. 5 shows six examples of breast cancer detection performed using the proposed framework (A two-stage Transfer Learning). All examples are obtained from the INbreast dataset. Tables VI, VII and VIII show the results of the proposed system using different learning rates, weighting factors and focusing parameters, respectively.

TABLE VI. THE PERFORMANCE OF THE PROPOSED FRAMEWORK WITH DIFFERENT LEARNING RATE (INBREAST DATASET)

Learning Rate	**Pretrained Dataset**	TPR @FPPI
0.000001	CBIS-DDSM	0.95@1.67
0.000005	CBIS-DDSM	0.96 @1.67
0.00001(best)	CBIS-DDSM	0.99 @1.67
0.00005	CBIS-DDSM	0.91 @1.67
0.0001	CBIS-DDSM	0.89 @1.67

TABLE VII. THE PERFORMANCE OF THE PROPOSED FRAMEWORK WITH DIFFERENT WEIGHTING FACTOR (INBREAST DATASET)

Weighting Factor	**Pretrained Dataset**	TPR @FPPI
0.15	CBIS-DDSM	0.88 @1.67
0.2	CBIS-DDSM	0.91 @1.67
0.25(best)	CBIS-DDSM	0.99 @1.67
0.3	CBIS-DDSM	0.98 @1.67
0.35	CBIS-DDSM	0.90 @1.67

TABLE VIII. THE PERFORMANCE OF THE PROPOSED FRAMEWORK WITH DIFFERENT FOCUSING PARAMETER (INBREAST DATASET)

Focusing Parameter	**Pretrained Dataset**	TPR @FPPI
1.5	CBIS-DDSM	0.96 @1.67
1.75	CBIS-DDSM	0.97 @1.67
2(best)	CBIS-DDSM	0.99 @1.67
2.25	CBIS-DDSM	0.95 @1.67
2.5	CBIS-DDSM	0.94 @1.67

V. CONCLUSION

In this research, a combination of two-stage transfer learning and a pre-trained object detector has been proposed for breast cancer detection. A one-stage CNN model called RetinaNet has been used. RetinaNet model is fast and efficient object detection model. In the first stage of transfer learning, the RetinaNet model is transferred onto another public dataset called CBIS-DDSM which is a new version of the DDSM dataset. In the second stage of transfer learning, the model is transferred and evaluated onto a small dataset of mammograms called INbreast. Comparisons with other current methods, our results show that the proposed framework can outperform existing cutting-edge methods in terms of TPR and FPPI metrics.

In future work, the authors plan to investigate how to use 3D imaging datasets with the proposed framework. They are more difficult, computationally demanding, and space-intensive than 2D datasets, however, in reality, such datasets show to be more informative than 2D datasets.

CONFLICT OF INTEREST

The authors declare no conflict of interest. Given his role as Editor-in-Chief, Branislav Vuksanovic had no involvement in the peer-review of this article and has no access to information regarding its peer-review.

AUTHOR CONTRIBUTIONS

Zeyad Q. Habeeb and Branislav Vuksanovic conducted the research and designed and implemented the experiments and they wrote the paper; The revised version of this paper was rewritten and improved by Zeyad Q. Habeeb, Branislav Vuksanovic and Imad Al-Zaydi; All authors had approved the final version.

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