Deep convolutional neural networks for detection and classification of tumors in mammograms

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***Abstract*—Automatic detection and classification of the masses in mammograms are still a big challenge and play a crucial role to assist radiologists for accurate diagnosis. In this paper, we propose a novel Computer-Aided Diagnosis (CAD).System based on one of the regional deep learning techniques, a ROI-based Convolutional Neural Network (CNN) which is called You Only Look Once (YOLO), in this work we used YOLO version three (YOLOv3). YOLO based CAD system can handle detection and classification simultaneously in one framework. It's a little bigger than last time but more accurate. The proposed CAD system contains four steps : preprocessing of mammograms, feature extraction utilizing deep convolutional networks, mass detection with confidence, and finally mass classification using fully connected neural networks (FC-NNs).**

***Index Terms*—Breast Cancer; Mass Detection and Classification; Computer Aided Diagnosis; Deep Learning; YOLO**

I. Introduction

Breast cancer is one of the most leading cancers for women. In 2016, about 246,660 women were diagnosed with breast cancer which is considered as the highest level of 29% among other kinds of cancers [1]. For the expected deaths, breast cancer is the second highest in women which alone accounts 14% against other cancer types [1]. Early detection with correct diagnosis is extremely important to increase the survival rate. In clinical practice, mammography is a widely used diagnostic tool to screen breast cancer. To correctly detect and diagnose breast cancer (benign or malignant), radiologists face challenges due to the large amount of breast images they have to examine daily and the difficulty of reading them (detecting the breast masses and correctly diagnosing them). Thus, computer-aided detection and diagnosis (CAD) are essential through which a second opinion can be provided to physicians to aid and support their decisions. The state of art indicate, In 2016, J. Virmani et al. developed a CAD system to recognize the breast densities [2]. They extracted different statistical texture features from the mass ROIs with different length of Laws' texture energy masks. The results of this CAD system was achieved using Support Vector Machine (SVM) and Probabilistic Neural Network (PNN) classifiers with classification accuracies of 94.4% and 92.5%, respectively. In 2016, C. Muramatsu et al. utilized texture attributes to distinguish between benign and malignant masses [3]. They proposed an ROI-based feature technique called Radial Local Ternary Patterns (RLTP) which represent the orientation of edge pattern from the center of mass. These RLTP feature sets were compared to ordinary Local Ternary Patterns (LTP), Rotation Invariant Uniform (RIU) LTP, wavelet features, and texture attributes from the Gray Level Co-occurrence Matrix (GLCM). Their CAD system performance of NN overcame Random Forest (RF) and SVM classifiers by 0.9, 0.895, and 0.881 in terms of areas under the receiver operating characteristic curves (AUC), respectively. In 2017, H. Li et al. developed a CAD system based on local contour features to classify benign and malignant masses [4]. They converted the 2D contour of the masses into 1D features. Four different subsections were generated by segmenting the whole 1D signature. New features of Root Mean Square (RMS) slope, describing the contour roughness, were extracted from each subsection besides the fractal dimension and the mean to standard deviation ratio features. Higher classification accuracy of 99.66% was achieved using SVM compared with 99.60% and 92.47% in the case of NN and k-Nearest Neighbors (K-NN), respectively. In 2017, S. A. Taghanak et al. proposed a deep auto-encoder network for multi-objective optimization [5]. Their goal was to reduce the dimensionality of features. They extended the conventional auto-encoder to get an optimal solution with more prominent features which in results minimized both mean squared reconstruction and classification errors. Their auto-encoder achieved the classification accuracy of 98.45% for 12 classes. As an alternative to conventional classifiers that utilize hand-crafted features, deep learning techniques can learn prominent features from the entire data

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[6, 7]. Recently, deep learning is gaining a lot of attention in the field of machine learning. It has been also employed in the field of CAD for breast cancer to overcome some of the limitations of the conventional CAD systems mentioned above. It is considered that deep learning methods can learn a set of high-level attributes and provide a high recognition accuracy instead of using handcrafted features. In 2016, Z. Jiao et al. developed a CAD system based on Convolutional Neural Network (CNN) to classify benign and malignant masses of breast cancer. They utilized the combination of low and high level deep features from two different CNN layers to train their model [6]. Their CAD system succeeded to classify the breast masses with classification accuracy of 96.7%. In 2016, J. Arevalo et al. developed a CNN framework to address the mass lesions of mammograms [7]. The ability of CNN model was investigated against the Histogram of Oriented Gradient (HOG) and Histogram Gradient Divergence (HGD) methods which extracted the features from the histogram. Their CAD system performance achieved AUC of 0.86 compared with 0.796 and 0.793 in the cases of HOG and HGD, respectively. In 2015, N. Dhungel et al. developed an algorithm using a cascade of deep learning and RF to detect the suspicious regions in mammograms [8]. Their algorithm consisted of multi-scale Deep Belief Network (DBN) to select all potential suspicious regions, CNN to keep the correct candidates of those regions, and RF to reduce false positive of the detected regions. Their approach achieved 96% of the true positive cases and 87% of the false positive cases. In 2017, N. Dhungel et al. proposed a total system for detection, segmentation, and classification of the breast masses [9]. They utilized the detected masses from [8] to segment the contours of the actual masses via a deep learning structure followed by Conditional Random Field (CRF). Thereafter, the segmented masses were refined using the Chan-Vese active contour model. Finally, a classical CNN classifier was pre-trained for regressing hand-crafted features and subsequently fine-tuned the pre-trained model. Their system showed an overall segmentation accuracy of 85%. Meanwhile, the performance of their system achieved 91% and 76% in terms of classification accuracy and AUC, respectively. In 2016, T. Kooi et al. employed a deep CNN to classify ROIs for malignant masses [10]. They investigated the power of CNN against the experiences of four radiologists. CNN exhibited its effective ability to recognize the malignant lesions with AUC of 0.87 against 0.84 in the case of radiologists. In 2016, M. Al-antari et al. developed a CAD system utilizing a DBN classifier to distinguish between three different regions of breast cancer (normal, benign, and malignant), whereas these masses are automatically classified [11]. The capability of DBN was presented against traditional predictors and produced the recognition rate of 92.33%. In 2016, A.-B. Ayelet et al. developed a region-based CNN (R-CNN) method to address the issue of tumor detection and classification [12]. In their work, the mammograms were first preprocessed by removing pectoral muscles and extracting the fibro-glandular. The entire images were divided into multiple overlapped parts. Then, their R-CNN was trained to detect the tumor region and to classify the tumor as benign or malignant. Their results achieved accuracy of 72% and 77% in terms of tumor detection and classification, respectively. In 2017, Y. Qiu et al. built a traditional CAD system to classify the breast masses into benign or malignant [13]. They utilized three convolutional layers to extract the features from 560 resampled ROIs. These features are connected to a multiple layer perceptron classifier with only one hidden layer and one logistic regression layer. Their proposed CAD system produced an overall AUC of 79%. In 2017, G. Carneiro et al. developed an automated deep learning model to examine the two-view of unregistered mammographic images (CC and MLO) [14]. Both views of each breast image with the segmented maps of their mammogram lesions (micro-calcifications and masses) were fed in the convolutional network model. Their system achieved 90% and 70% in term of volume under the ROC surface for both semi-automated and fully automated technique, respectively. In this paper, a novel CAD system is proposed for breast masses detection and classification by employing a novel regional convolutional neural network called You Only Look Once (YOLO) [15]. We augmented the original database of 600 cases by rotating the original mammograms using three different angles for training and testing. YOLO offers a powerful functionality in that it can learn ROIs and their background at the same time. Thus, our proposed CAD system can achieve both detection and classification of breast masses in a single framework. We evaluate the proposed YOLO-based CAD system through using two different datasets (original and augmented datasets). Our proposed system exhibits an overall accuracy of detection and classification of 99.7% and 97%, respectively. This paper proceeds as follows. First, we present the overall system with the information of original and augmented databases for training and testing. Second, the details of YOLO-based CAD system for detection and diagnosis of breast cancer masses is explained. Then, we evaluate the performance of our proposed CAD system throughout five-fold cross validation. Finally, we discuss about the results against other CAD works employing classifiers such as DBN and CNN. Finally, conclusion of this work is given.

II. METHODS

A. *Our Proposed CAD System YOLOv3-based*

Schematic diagram of the proposed CAD system is demonstrated in Figure 1. Our proposed YOLO-based CAD system for simultaneous breast masses detection and classification consists of four main stages: mammogram preprocessing, feature extraction utilizing multi convolutional deep layers, mass detection with confidence model, and fully connected neural network (FC-NN) for breast mass classification.

B. *Original Database*

In this study, we utilized a database of mammograms from Digital Database for Screening Mammography (DDSM) [16] to train and test our YOLO-based CAD system. The DDSM database is created by the University of South Florida and

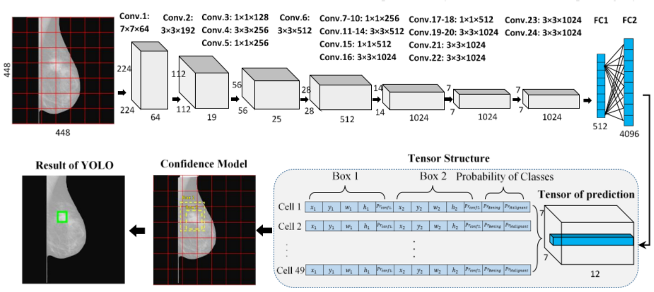


Figure 1. Scheme of YOLO-BASE CAD system

it has been widely utilized in breast research purposes [6, 11, 17]. It contains 2,620 cases which are organized in 43 volumes. Four mammograms are collected for each case with two different views: mediolateral oblique (MLO) and cranio-caudal (CC). Each mammogram contains suspicious lesions associated with information of the ground truth. In this work, we have randomly selected a set of 600 mammograms from DDSM database which are equally categorized to benign and malignant cases.

C. Augmented Database

In fact, deep learning requires large amount of data for proper training. However, small size of medical dataset is one of the most challenging to handle deep learning approaches. Due to this, we used a technique of augmentation to increase the training data. Augmentation is a process that generates new instances from the original data using different transformation methods such as rotation, translation, and scale [6, 18, 19]. In order to minimize the overfitting problems, that may appear when small size of dataset is utilized via deep learning techniques, we have augmented our dataset three times by rotating the mammograms with angles of 90 o , 180 o , and 270 o as successfully applied in [6, 14, 18, 19]. Thus, a total of 2,400 mammograms (i.e., the original mammograms along with their augmented data) are used to train and test the proposed YOLO-based CAD system. The half of mammograms represents the benign and the other half for the malignant. All original and augmented mammograms are randomly mixed together in order to avoid any classification bias of our CAD system.

D. Data Preprocessing

In this work, mammograms and their ROIs (i.e., masses) must be learned by YOLO. In preparation of input data, we first applied the multi-threshold peripheral equalization technique [20, 21] to remove the effect of breast compression that occurred during the examining stage [22]. The peripheral density correction is achieved by the following steps. First, the mask containing breast region is generated using the Otsu thresholding technique. Then, the mask image is multiplied with the blurred image which is produced by applying 2D Gaussian low pass filter to original breast image. Then, the normalized thickness profile (NTP) is derived using different threshold values. These threshold values are computed with respect to the average of blurred image. Finally, the peripheral density correction image is achieved by dividing the original mammogram over the NTP image [23]. This procedure improves the characteristics of the mammograms by eliminating the background and irrelevant data as presented in the previous work [11, 23]. In order to achieve a high performance of CAD system, training and testing datasets are normalized in the range of [0, 1] as presented in [6, 24]. In DDSM, the mammograms exist with different image sizes [16], hence training and testing datasets are resized to a size of 448×448 as in [15].

E. What is YOLO? and what is different between YOLO & YOLOv3

You Only Look Once (YOLO) is one of the state-of-the-art deep learning techniques [15]. It is able to detect and classify objects in the entire images at the same time. Unlike previous detection techniques that applied the classifier to multiple regions of the image [8], YOLO utilizes a single convolutional neural network to the whole image. This approach divides the input image into sub-regions and predicts multiple bounding boxes with their class probabilities for each region. Unlike traditional R-CNN that requires many networks for all the extracted regions, YOLO utilizes the entire mammograms so that the contextual information of the predictors and their aspect are completely encoded with a single network in both training and testing time [15]. YOLO has several advantages over other detection systems. This is due to that YOLO looks the image once and does not require a complex pipeline, it is extremely fast and its predictions are informed by global context in the data. YOLOv3 by Joseph Redmon, Ali Farhadi, University of Washington present some updates to YOLO! We made a bunch of little design changes to make it better. how it work? Prior detection systems repurpose classifiers or localizers to perform detection. They apply the model to an image at multiple locations and scales. High scoring regions of the image are considered detections. We use a totally different approach. We apply a single neural network to the full image. This network divides the image into regions and predicts bounding boxes and probabilities for each region. These bounding boxes are weighted by the predicted probabilities[30] Our model has several advantages over classifier-based systems. It looks at the whole image at test time so its predictions are informed by global context in the image. It also makes predictions with a single network evaluation unlike systems like R-CNN which require thousands for a single image. This makes it extremely fast, more than 1000x faster than R-CNN and 100x faster than Fast R-CNN[30] We also trained this new network that's pretty swell. It's a little bigger than last time but more accurate. It's still fast though, don't worry. At 320 × 320 YOLOv3 runs in 22 ms at 28.2 mAP, as accurate as SSD but three times faster. When we look at the old .5 IOU mAP detection metric YOLOv3 is quite good. It achieves 57.9 AP 50 in 51 ms on a Titan X, com-pared to 57.5 AP 50 in 198 ms by RetinaNet, similar performance but 3.8 × faster. Moreover, you can easily tradeoff between speed and accuracy simply by changing the size of the model, no retraining required!

F. YOLO Architecture

YOLO is a unified system that is able to detect the potential ROIs and directly predict their class probabilities from an entire whole image [15, 25]. Our proposed YOLO-based CAD highlights two main issues of finding out the mass locations and classification their types of benign or malignant.

YOLO starts with dividing an input mammogram into N×N non-overlapped grid cells. Thus, each grid cell is responsible to detect the potential mass belonging to that cell. As successfully applied in [15], two bounding boxes with their confidence scores are utilized to represent each grid cell. Confidence is expressed as the probability of the existing mass multiplied with the percentage of the intersections over union (IOU) between the ground truth and the predicted boxes as follows:

$$Confidence = Prob(mass) \times IOU_{predicted}^{groundtruth} \quad (1)$$

Also, the detected mass is recognized as benign or malignant depending on the conditional class $Prob(class_i|mass)$ for the corresponding cell [15]. Then, the confidence score for probability each specific class is estimated as follows:

$$\begin{aligned} Confidencescore &= Prob(Class_i|mass) \times Confidence \\ &= Prob(Class_i) \times IOU_{predicted}^{groundtruth} \end{aligned} \quad (2)$$

where confidence score interprets model confidence in order to represent the mass that is involved in the predicted box and also how accurate of that mass is. This confidence score becomes zero when the grid cell does not contain any objects. YOLO is trained utilizing the entire breast image with its ROIs' information. For training, we prepare the training data with the ROI position and size information: the information of training data contains the center position (x, y), width (w), height (h), and class label of the masses.

G. Training

We still train on full images with no hard negative mining or any of that stuff. We use multi-scale training, lots of data augmentation, batch normalization, all the standard stuff. We use the Darknet neural network framework for training and testing. The trained and tested this CAD system need to use two different datasets (original and augmented datasets). All results of both detection and classification the breast abnormalities are obtained by training YOLO with the augmented dataset. In one exception, we compare the effect of data augmentation against the case of using the original dataset. To avoid any bias in training and testing, we first optimized the parameters of the proposed YOLO-based CAD system using only the training dataset (80% of the data). Then, the final system performance was evaluated using only the testing dataset (20% of the data) [32]. It is shown that the concept of transfer learning is effective in training a deep net as in [14, 15, 26, 27, 28]. As this transfer learning was applied to DDSM in [6, 14], we trained our YOLO-based CAD system with the pre-trained weights with a large computer vision ImageNet dataset [29]. Subsequently, it was fine-tuned (re-trained) with the training augmented mammograms.

To validate our results, we performed a k-fold cross validation ($k = 5$) to ensure that every mammogram in our dataset gets to be in a test set exactly once and to minimize the bias error that may occur during the classification stage. The dataset is randomly divided into five subsets where each subset is formed by 10% benign and 10% malignant cases. One of the subsets (20% of dataset) is utilized as a testing set while the other subsets (80% of dataset) are considered together as a training set. This means we trained our YOLO-based CAD system five times to get the performance of the CAD system. For each k-fold, the computation time took almost four days to perform the training stage. However, the decoding (detection and classification) for each mammogram takes only less than three seconds. Thus, the proposed CAD-system seems to be feasible and reliable to apply in the future for clinical applications. The results for both masses detection and classification are evaluated as an average of the 5-fold cross validation results.

H. Feature Extractor

We use a new network for performing feature extraction. Our new network is a hybrid approach between the network used in YOLOv2, Darknet-19, and that newfangled residual network stuff. Our network uses successive 3 × 3 and 1 × 1 convolutional layers but now has some shortcut connections as well and is significantly larger. It has 53 convolutional layers.This new network is much more powerful than Darknet-19 but still more efficient than ResNet-101 or ResNet-152. Each network is trained with identical settings and tested at 256 × 256, single crop accuracy. Run times are measured on a Titan X at 256 × 256. Thus Darknet-53 performs on par with state-of-the-art classifiers but with fewer floating point operations and more speed. Darknet-53 is better than ResNet-101 and 1.5× faster. Darknet-53 has similar performance to ResNet-152 and is 2× faster. Darknet-53 also achieves the highest measured floating point operations per second. This means the network structure better utilizes the GPU, making it more efficient to evaluate and thus faster. That's mostly because ResNets have just way too many layers and aren't very efficient [30.]

III. RESULTS

A. Bounding Box prediction

This system predicts bounding boxes using dimension clusters as anchor boxes. The network predicts 4 coordinates for each bounding box, t_x, t_y, t_w, t_h . If the cell is offset from the top left corner of the image by (c_x, c_y) and the bounding

	Type	Filters	Size	Output
	Convolutional	32	3 × 3	256 × 256
	Convolutional	64	3 × 3 / 2	128 × 128
1×	Convolutional	32	1 × 1	
	Convolutional	64	3 × 3	
	Residual			128 × 128
	Convolutional	128	3 × 3 / 2	64 × 64
2×	Convolutional	64	1 × 1	
	Convolutional	128	3 × 3	
	Residual			64 × 64
	Convolutional	256	3 × 3 / 2	32 × 32
8×	Convolutional	128	1 × 1	
	Convolutional	256	3 × 3	
	Residual			32 × 32
	Convolutional	512	3 × 3 / 2	16 × 16
8×	Convolutional	256	1 × 1	
	Convolutional	512	3 × 3	
	Residual			16 × 16
	Convolutional	1024	3 × 3 / 2	8 × 8
4×	Convolutional	512	1 × 1	
	Convolutional	1024	3 × 3	
	Residual			8 × 8
	Avgpool		Global	
	Connected		1000	
	Softmax			

Figure 2. Darknet-53

box prior has width and height p_w, p_h , then the predictions correspond to:

$$
\begin{aligned}
b_x &= \sigma(t_x) + c_x \\
b_y &= \sigma(t_y) + c_y \\
b_w &= p_w \\
b_h &= p_h \exp(t_h)
\end{aligned}
$$

During training we use sum of squared error loss. If the ground truth for some coordinate prediction is $\hat{t}^*$ our gradient is the ground truth value (computed from the ground truth box) minus our prediction: $\hat{t}^* t^*$. This ground truth value can be easily computed by inverting the equations above. YOLOv3 predicts an objectness score for each bounding box using logistic regression. This should be 1 if the bounding box prior overlaps a ground truth object by more than any other bounding box prior. If the bounding box prior is not the best but does overlap a ground truth object by more than some threshold we ignore the prediction, following.We use the threshold of .5. Unlike our system only assigns one bounding box prior for each ground truth object. If a bounding box prior is not assigned to a ground truth object it incurs no loss for coordinate or class predictions, only objectness.We predict the

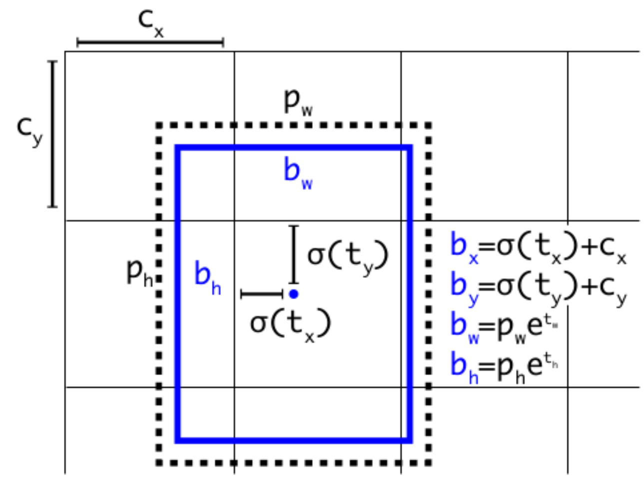


Figure 3. Bounding boxes with dimension priors and location prediction

width and height of the box as offsets from cluster centroids. We predict the center coordinates of the box relative to the location of filter application using a sigmoid function [30].

B. Class Prediction

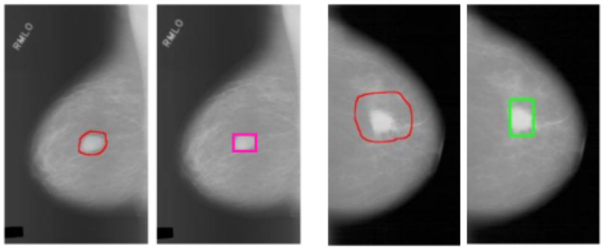
Each box predicts the classes the bounding box may contain using multilabel classification. We do not use a softmax as we have found it is unnecessary for good performance, instead we simply use independent logistic classifiers. During training we use binary cross-entropy loss for the class predictions. This formulation helps when we move to more complex domains like the Open Images Dataset. In this dataset there are many overlapping labels. Using a softmax imposes the assumption that each box has exactly one class which is often not the case. A multi-label approach better models the data. [30]

C. Predictions Across Scales

YOLOv3 predicts boxes at 3 different scales. Our system extracts features from those scales using a similar concept to feature pyramid networks.From our base feature extractor we add several convolutional layers. The last of these predicts a 3-d tensor encoding bounding box, objectness, and class predictions[30].

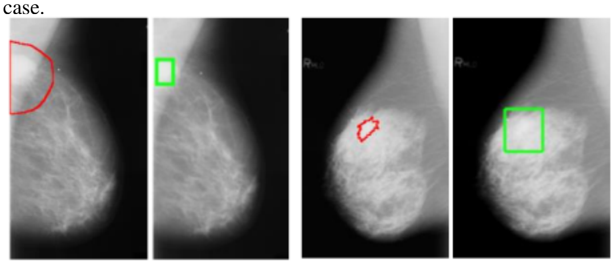
IV. DISCUSSION

In this study, we have developed a deep learning YOLO-based CAD system which detects the locations of potential masses on mammograms and classifies them into benign or malignant simultaneously. The recent deep learning CAD systems only addressed the diagnosis task of the extracted patches from mammograms [6, 7, 10, 11, 13, 23]. In contrast, the proposed YOLO-based CAD system could handle both detection and classification at the same time using whole breast image. Figures 4 and 5 show the capability of the proposed CAD system to detect the potential breast masses and produce the proper diagnosis for each mammogram (benign or malignant).



(a) (b) (c) (d)

Figure 4. Mass detection. (a) and (b) show the ground-truth mass and detected from new proposed method for a benign case, while (c) and (d) for a malignant case.



(a) (b) (c) (d)

Figure 5. Mass detection and classification. (a) and (c) show the ground-truth mass over the pectoral muscle and the detected by new proposed method, respectively. (b) and (d) present the ground-truth mass surrounding by dense tissue and the detected by new proposed CAD.

Table I
5-FOLD CROSS VALIDATION PERFORMANCE OF THE MASS DETECTION VIA THE PROPOSED YOLO-BASED CAD SYSTEM

Fold Test	**Benign**		**Malignant**		**Total**	
	true	false	true	false	true	false
1^{st} fold	**240**	**0**	**240**	**0**	**480**	**0**
	100%	0.0%	100%	0.0%	100%	0.0%
2^{nd} fold	**237**	**3**	**239**	**1**	**476**	**4**
	98.75%	1.25%	99.58%	0.42%	99.17%	0.83%
3^{rd} fold	**238**	**2**	**240**	**0**	**478**	**2**
	99.17%	0.83%	100%	0.0%	99.58%	0.42%
4^{th} fold	**239**	**1**	**240**	**0**	**479**	**1**
	99.58%	0.42%	100%	0.0%	99.79%	0.21%
5^{th} fold	**240**	**0**	**240**	**0**	**480**	**0**
	100%	0.0%	100%	0.0%	100%	0.0%
Average (%)	**99.50**	**0.50**	**99.92**	**0.08**	**99.71**	**0.29**

First, it could reveal the breast masses which are existed over the pectoral muscle as shown in Figure 5(b). Second, the proposed methodology successfully identified breast masses in the dense tissues as shown in Figure 5(d). In fact, both of these challenges are due to the high intensities (more bright) among the pectoral muscle and dense tissue regions compared to normal breast tissue.

The results of Table 1 show the analysis of both detection and classification of the breast masses throughout 5-fold cross validation.

It is previously shown that training with augmented data

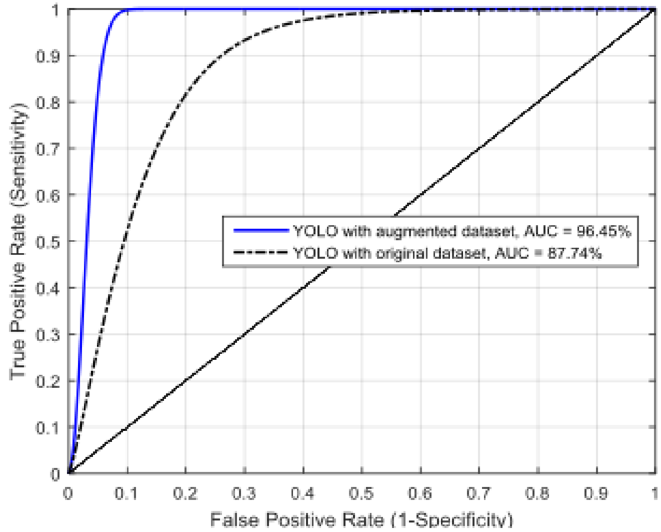


Figure 6. ROC curves of the proposed YOLO-based CAD system with the augmented dataset against the original dataset

improves the performance of breast masses detection and classification [6, 14, 18, 19]. The overall accuracy performance increased from 85.5% with the 600 original mammograms to 97% with the 2,400 augmented mammograms as shown in Figure 5(b) . These results demonstrate that the YOLO-based CAD system is effective to achieve high accuracy in both detection and classification of the abnormalities at the same time.

In order to show how robust the proposed YOLO-based CAD system is, we compare the results with the latest studies employing DBN and CNN. Comparison with the conventional classifiers that do not utilize deep learning is also provided to present the efficiency of the deep learning algorithms. In the previous work [23] that utilized same kind of DDSM mammograms, a DBN-based CAD system was applied and compared its outcomes against the conventional Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), and Neural Network (NN) classifiers. Statistical handcrafted features are excerpted from the extracted masses. That study investigated the effect of features dimensionality reduction through different feature selection methods. As different of our proposed CAD system that utilized the whole mammograms for the convolutional layers, they only used the ROIs of the cropped masses. Combination of the middle level and high level features are utilized to train and test the CAD system based CNN. The performance of CNN shows it capability to classify the masses into benign or malignant with overall accuracy of 96.7%. Actually, this classification results are highly comparable with ours. In contrast, only our proposed YOLO-based CAD system can detect the masses in mammograms besides predicting their types compared with the conventional CNN. Our proposed technique should be feasible as a CAD system capable of detection and classification the abnormalities of the breast images. Finally, we present a comparison of the effect of utilizing augmented data instead of original ones. In [18], the mass dataset are augmented utilizing three transformation types: rotation, translation, and scaling. Normal and malignant cases are classified by applying CNN to the mass patches with a size of 250×250. Their AUC results of the CNN without the augmented dataset achieved 87.5%, while it reached to 92.9% with the augmented dataset. This improvement rate is comparable with our AUC results from 87.74% to 96.45%.

V. CONCLUSION

In this paper, we present YOLO-based CAD system for breast mass detection and cancer classification. The proposed CAD system incorporates a ROI-based CNN approach which utilizes the convolutional layers followed by fully connected neural networks to detect the proper location of the mass and to distinguish the tumor types: benign or malignant. Our results provide feasible and promising results in term of detecting the location of benign and malignant masses and recognize their proper classes as well. Furthermore, the YOLO-based CAD system detects the masses existing over the pectoral muscle or surrounding by the dense tissue in the mammograms which are considered as most challenging cases of breast cancer CAD. The next step of the presented CAD system is to be tested in practice for its real validity.

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