As per UGC guidelines an electronic bar code is provided to seure your paper

International Journal for Modern Trends in Science and Technology, 8(04):416-419, 2022

ISSN: 2455-3778 online
DOI: https://doi.org/10.46501/IJMTST0804070
Available online at: http://www.ijmtst.com/vol8issue04.html

Deep Learning Computer-Aided Diagnosis System to Screen Digital X-Ray Mammograms

Prasanthi Avanigadda | Shaik Abid | Yadali Venkata Sai Ashik | Nuthi Gopi Chand

Department of Electronics and Communication Engineering, R.V.R & J.C College of Engineering, Guntur, A.P, India.
Corresponding Author Email ID: prasanthi.avanigadda01@gmail.com

To Cite this Article
Prasanthi Avanigadda, Shaik Abid, Yadali Venkata Sai Ashik and Nuthi Gopi Chand. Deep Learning Computer-Aided Diagnosis System to Screen Digital X-Ray Mammograms. International Journal for Modern Trends in Science and Technology 2022, 8(04), pp. 416-419. https://doi.org/10.46501/IJMTST0804070

Article Info
Received: 19 March 2022; Accepted: 17 April 2022; Published: 22 April 2022.

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. Breast cancer is one of the most common cancers worldwide among women. Mammography is the basic tool available for screening to find the abnormality at the earliest. An integrated CAD system of deep learning detection and classification is proposed aiming to improve the diagnostic performance of breast lesions. First, a deep learning YOLO detector is adopted and evaluated for breast lesion detection of mammograms and distinguishes between the malignant and benign lesions without any human intervention. Then a deep learning classifier namely Inception v3 is modified and evaluated for breast lesion classification.

KEYWORDS: Breast lesions; Detection; Classification; Computer-Aided Diagnosis (CAD); You Only Look Once (YOLO); Inception v3; Deep Learning;

1. INTRODUCTION

Nowadays, breast cancer is considered one of the most common cancers threatening women's life especially women after skin cancer. Besides that, as expected by WHO, in 2025 the number of cases that will be diagnosed with breast cancer will be nearly 19.3 million cases. //Mammography is at present the best available technique for early detection of breast cancer. There are two classes of lesions, benign and malignant, and if there is no lesion in the breast it is considered normal. The benign lesion cells are non–cancerous cells and grow only locally and cannot spread by invasion. While malignant lesions are cancerous cells and they have the ability to multiple uncontrollably, to spread to various parts of the body and invade surrounding tissue (DL in breast).

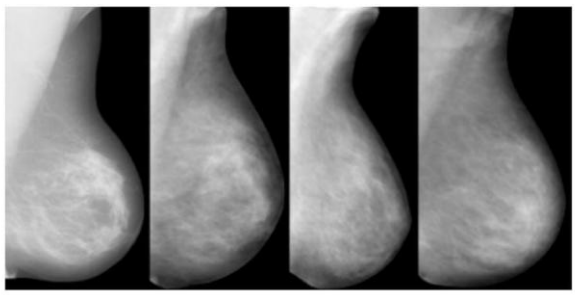

Fig. 1 Example of Mammogram images

The development of accurate Computer-Aided Diagnose (CAD) systems is considered the second essential opinion that can be used by physicians to aid and support their decisions towards the masses detection and classification.

We used You Only Look Once (YOLO V4) to detect the masses. Where python programming language is used to

train and test the model. We have trained the model using large set of data. Where after raining the model we obtained the trained weights. These trained weights are further used for testing to detect the masses. As for the classification of masses we used Inception v3. Inception helps classification of objects in the world of computer vision. The Inceptionv3 architecture has been reused in many different applications

The rest of the paper is organized as follows. In the dataset section, then methodology used for the detection and classification are explained. Next we can see the training and testing results of mass detection and classification. It is followed by the conclusions and references.

2.DATA SET

There are different types of datasets available for mass detection and classification. INbreast dataset, DDSM, Curated Breast Imaging Subset of DDSM Dataset (CBIS-DDSM), e Mammographic Image Analysis Society (MIAS) Dataset and Breast Cancer Digital Repository (BCDR) Dataset.

A. DDSM

In this study, we utilized a database of mammograms from Digital Database for Screening Mammography (DDSM) to train and test our YOLO-based CAD system. The DDSM database is created by the University of South Florida and it has been widely utilized in breast research purposes. 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 craniocaudal (CC). Each mammogram contains suspicious lesions associated with information of the ground truth. In this work, we have randomly selected a set of 6,000 mammograms from DDSM database which are equally categorized to benign and malignant cases and it also contains normal images.

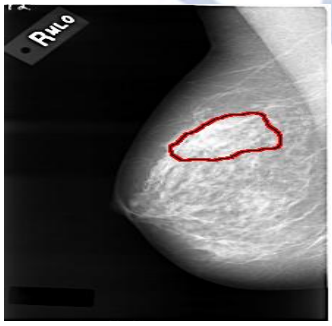

Fig. 3 DDSM dataset image

The DDSM is a database of 2,620 scanned film mammography studies. It contains normal, benign, and malignant cases with verified pathology information. The scale of the database along with ground truth validation makes the DDSM a useful tool in the development and testing of mammograms. DDSM is a resource for use by the mammographic image analysis research community. Some of the cases in this database were collected from the Nijmegen Database. Image annotations include pixel level boundary of the findings.

For training we need to clone the darknet and made some changes in the yolov4 configuration file. The configuration file consists of number of layers,
batch size, subdivisions, filters and channel value. We have to change these parameters according to our dataset. In order to train the images we require pre-trained weights. By using both the configuration file and pre-trained weights we perform training of images. After training we obtain the trained weights, which we are used further to perform testing of images.

3.METHODOLOGY

You Only Look Once (YOLO) is one of the state-of-the-art deep learning techniques. It is able to detect and classify objects in the entire images at the same time. It is also used for the detection and segmentation of skin lesions such as melanoma, benign nevi, and seborrheic keratoses that exist in dermoscopic images with a good sensitivity of 90.82%. The object detection task consists of determining the object location in terms of the bounding box surrounding it on the input image, as well as classifying those objects.

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. There are many versions in yolo they are yolo v1, yolo v2, yolo v3, yolo v4. we mainly use yolo v4 which has high accuracy results.

Versions of YOLO

YOLO v1 is the first version created. But due to bad performance when there are groups of small objects and 49 objects only can be detected by the 7×7 grid since each cell can detect only 1 object. Since each cell cannot predict more than one object, this results in a close object detection problem occurring when near small masses

exist in the same cell. If the mass is somehow large and located in more than one cell, it will be detected more than one time. YOLO-V1 suffers from the high localization error and the low recall.

YOLO v2 is developed. YOLO-V2 architecture is still missing some of the most important components such as it cannot detect the small objects that exist in an image in an accurate way that are now stapled in most of the state-of-the art detection algorithms like the residual blocks, skip connections, and sampling. The output prediction is carried out at the last layer. So, the YOLO v2 is further developed to create YOLO v3.

YOLO v3 makes detection at three different scales. Therefore small objects also detected easily. It is a little bigger model which takes more time for training than the previous 2 versions. Close objects problem is somehow handled but some limitations still exist for very close objects. YOLO v3 is better but not faster and stronger than YOLO v2.

Hence, YOLO v3 is further developed to create YOLO v4 which is faster, stronger and even detect small objects easily.

The YOLO's detection network is merged with ResNet and InceptionV3 networks for classification and it is proved from the experimental results that YOLO and Inception are more accurate than ResNet to classify the detected masses achieving overall accuracy of 90.5% for classifying the detected masses. So, we have used Inceptionv3 for classification instead of ResNet.

Comparison Criteria	YOLO-V1	YOLO-V2	YOLO-V3	YOLO-V4
of Convolutional Layers	24	19	53	53
Fully connected layers	2	0	0	0
of YOLO Layers	0	1	3	4
short-cut layers and residual blocks	✗	✗	√	√
Batch normalization on all convolutional layers	✗	√	√	√
Grid cell size	7	13	13	13
Frame Per Second (FPS)	45	40-90	30	443
Anchors boxes for multiple detections of objects per one grid cell	✗	√	√	√
of objects can be detected per cell	1	≥1	≥1	≥1
Non-Maximal Suppression (NMS)	✗	√	√	√
Resizing during training for different resolutions predictions	✗	√	√	√

Fig. 3 Comparision table of Yolo versions

The Receiver Operating Characteristics (ROC) metric is used to evaluate the model's classification performance on the public INbreast dataset by using YOLO classification layers versus InceptionV3 and ResNet features extractors.

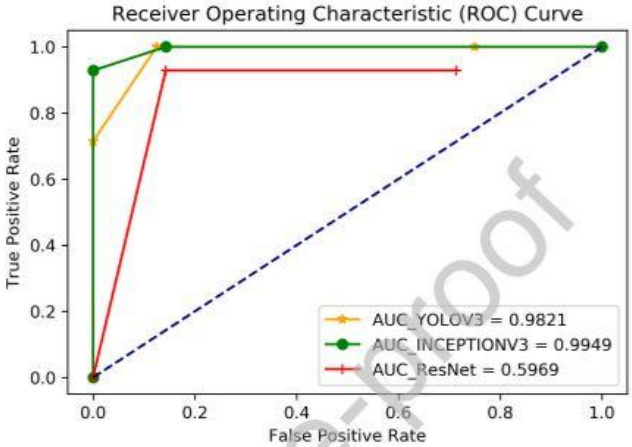

Fig. 3 ROC curve

4.TRAINING AND TESTING RESULTS

Yolo format of image as input to make the experiments easy to be conducted with different resolution and sizes, the mass ground truth coordinates are normalized relative to the width and height of the image to be from [0.0 to 1.0]. The mass class and its coordinates represented in x, y, width, and height of the mass are saved to be used as an input to the model, representing the case annotation. Finally, the mammograms are transformed into smaller resolutions to fit into the model. In this paper, different sizes are used for training which are 448×448, 608×608, and 832×832.

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 (i.e., 80% of the data). Then, the final system performance was evaluated using only the testing dataset (i.e., 20% of the data). It is shown that the concept of transfer learning is effective in training a deep net. As this transfer learning was applied to DDSM images, we trained our YOLO based CAD system with the pre-trained weights with a large computer vision ImageNet dataset. Subsequently, it was fine-tuned (i.e., re-trained) with the training augmented mammograms.

A.Steps to train Yolo v4

We then need to label each and every image of our training dataset using LabelImg software. • After Labelling the image a txt file will be Created. • After Labelling all the image the files are compressed into a folder and trained

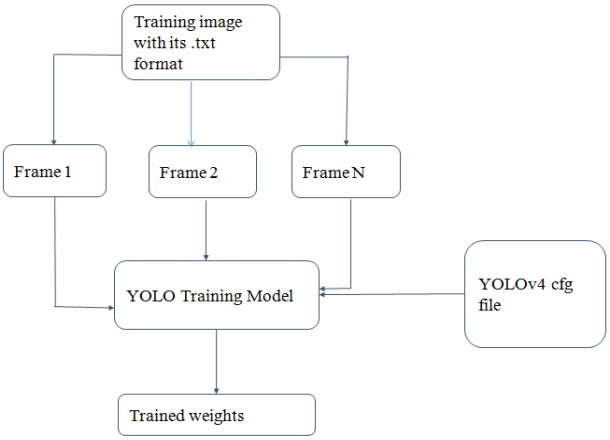

Fig. 4 Flow chart for training

In order to train the images we require pre-trained weights. By using both the configuration file and pre-trained weights we perform training of images. After training we obtain the trained weights, which we are used further to perform testing of images. The testing results are shown below.

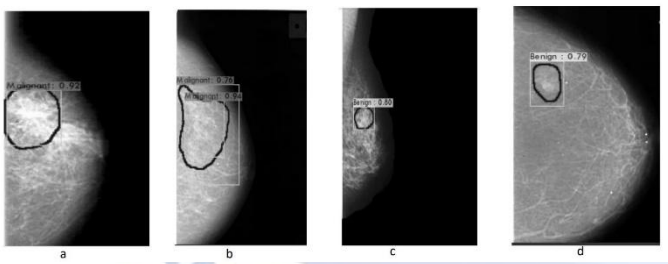

Fig. 4 figures a and b shows the detected masses for malignant case and c and d shows the detected masses for benign case

5. CONCLUSIONS

In this paper, we present YOLO-based CAD system for breast mass detection and Inception-V3 for 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.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

REFERENCES

[1] Mohammed A. Al-masni, Mugahed A. Al-antari, Jeong-min Park, Geon Gi, Tae-Yeon Kim, Patricio Rivera, Edwin Valarezo, Mun-Taek Choi, Seung-Moo Han, Tae-Seong Kim, Simultaneous Detection and Classification of Breast Masses in Digital Mammograms via a Deep Learning YOLO-based CAD System, Computer Methods and Programs in Biomedicine (2018).

[2] Ghada Hamed Aly, Mohammed Marey, Safaa Amin El-Sayed, Mohamed Fahmy Tolba, YOLO Based Breast Masses Detection and Classification in Full-Field Digital Mammograms, Computer Methods and Programs in Biomedicine (2020).

[3] M. A. Al-masni, Member, IEEE, M. A. Al-antari, Member, IEEE, J. M. Park, G. Gi, T. Y. Kim, P. Rivera, E. Valarezo, S.-M. Han, and T.-S. Kim, Detection and Classification of the Breast Abnormalities in Digital Mammograms via Regional Convolutional Neural Network (2017)

[4] G. R. Sinha and Bhagwati C. Patel, Medical Image Processing: Concepts and Applications, ISBN: 978-81-203-4902-5, Prentice Hall of India,2014.

[5] J. Redmon, S. Divvala, R. Girshick and A. Farhadi, "You only look once Unified, realtime object detection:" in IEEE Conference on Computer Vision and Pattern Recognition, 2016.

[6] D. Ribli, A. Horv´ath, Z. Unger, P. Pollner, I. Csabai, Detecting and classi fying lesions in mammograms with deep learning, Scientific reports 8 (1) (2018).

[7] A.-B. Ayelet, L. Karlinsky, S. Alpert, S. Hasoul, R. Ben-Ari and E. Barkan," A region based convolutional network for tumor detection and classification in breast mammography," in International Workshop on Large-Scale Annotation of Biomedical Data and Expert Label Synthesis, Athens, Greece, Springer International Publishing,2016, pp. 197-205.

[8] Ghada Hamed(B), Mohammed Abd El-Rahman Marey, Safaa El-Sayed Amin, and Mohamed Fahmy Tolba, Deep Learning in Breast Cancer Detection and Classification (2020).