Simultaneous Detection and Classification of Breast Masses in Digital Mammograms via a Deep Learning YOLO-based CA....

Article *in* Computer Methods and Programs in Biomedicine · April 2018

DOI: 10.1016/j.cmpb.2018.01.017

10 authors, including:

Mohammed Almasani
Kyung Hee University

Mugahed A. Al-antari
Kyung Hee University

Geon Gi
Kyung Hee University

Patricio Rivera
Kyung Hee University

Computer Methods and Programs in Biomedicine 157 (2018) 85–94

Contents lists available at ScienceDirect

Computer Methods and Programs in Biomedicine

journal homepage: www.elsevier.com/locate/cmpb

Simultaneous detection and classification of breast masses in digital mammograms via a deep learning YOLO-based CAD system

Mohammed A. Al-masni[a,1], Mugahed A. Al-antari[a,1], Jeong-Min Park[a], Geon Gi[a], Tae-Yeon Kim[a], Patricio Rivera[a], Edwin Valarezo[a], Mun-Taek Choi[b], Seung-Moo Han[a], Tae-Seong Kim[a,*]

[a] *Department of Biomedical Engineering, College of Electronics and Information, Kyung Hee University, Yongin, Republic of Korea*
[b] *School of Mechanical Engineering, Sungkyunkwan University, Republic of Korea*

ARTICLE INFO

Article history:
Received 11 August 2017
Revised 8 December 2017
Accepted 15 January 2018

Keywords:
Breast cancer
Mass detection and classification
Computer Aided Diagnosis
Deep learning
You Only Look Once (YOLO)

ABSTRACT

Background and objective: 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). Although most previous studies only deal with classification of masses, our proposed YOLO-based CAD system can handle detection and classification simultaneously in one framework.
Methods: The proposed CAD system contains four main stages: preprocessing of mammograms, feature extraction utilizing deep convolutional networks, mass detection with confidence, and finally mass classification using Fully Connected Neural Networks (FC-NNs). In this study, we utilized original 600 mammograms from Digital Database for Screening Mammography (DDSM) and their augmented mammograms of 2,400 with the information of the masses and their types in training and testing our CAD. The trained YOLO-based CAD system detects the masses and then classifies their types into benign or malignant.
Results: Our results with five-fold cross validation tests show that the proposed CAD system detects the mass location with an overall accuracy of 99.7%. The system also distinguishes between benign and malignant lesions with an overall accuracy of 97%.
Conclusions: Our proposed system even works on some challenging breast cancer cases where the masses exist over the pectoral muscles or dense regions.

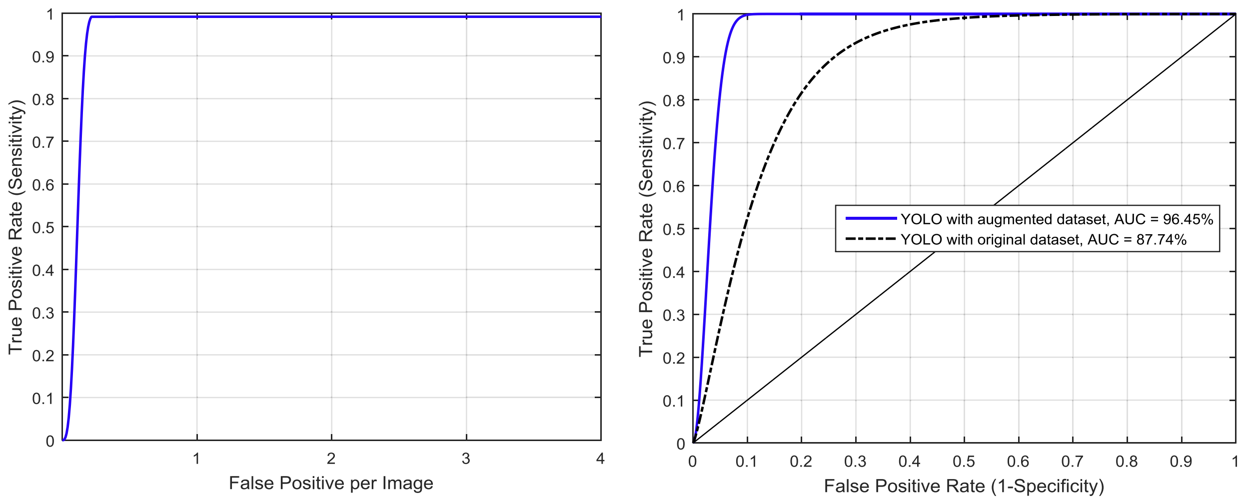
1. Introduction

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 (i.e., 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 (i.e., 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.

Several studies have been conducted to build CAD systems utilizing conventional recognizers which are attempted to differentiate the breast lesions. 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 dimensionality of these feature vectors was reduced using Principal Component Analysis (PCA). The first four components of the texture features were employed for classification. 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. uti-

* Corresponding author.
E-mail addresses: m.almasani@khu.ac.kr (M.A. Al-masni), en.mualshz@khu.ac.kr (M.A. Al-antari), jmpark@khu.ac.kr (J.-M. Park), geon@khu.ac.kr (G. Gi), kty@khu.ac.kr (T.-Y. Kim), patoalejor@khu.ac.kr (P. Rivera), edgivala@khu.ac.kr (E. Valarezo), mtchoi@skku.edu (M.-T. Choi), smhan@khu.ac.kr (S.-M. Han), tskim@khu.ac.kr (T.-S. Kim).
[1] Equally contributed to this work.

https://doi.org/10.1016/j.cmpb.2018.01.017
0169-2607/



(a) (b)

Fig. 7. (a) FROC curve performance of breast mass detection. (b) ROC curves of the proposed YOLO-based CAD system with the augmented dataset against the original dataset.

Table 4
Classification performance of present proposed YOLO-based CAD system against conventional classifiers, DBN, and CNN.

Reference	Method	Database (No. images)	Prediction classes	Mass detection accuracy (%)	Classification accuracy (%)
Al-antari et al. [23]	LDA	DDSM (168)	Normal / Benign /	86.00	78.57
	QDA		Malignant		76.19
	NN				84.52
	DBN				90.48
Jiao et al. [6]	CNN	DDSM (2400)	Benign / Malignant	X	96.70
Present study	**YOLO**	**DDSM (2400)**	**Benign / Malignant**	**99.7**	**97.00**

nique, all the extracted features are utilized, without the need of features reduction, to train and test the CAD system. It is clearly shown that how the DBN overcomes the conventional classifiers with overall accuracy of 90.48%. Also, a comparison study between random forest (RF) classifier against CNN was investigated in [18]. Different kinds of features set are manually extracted from the mass patches to train RF classifier. Each features set are individually trained and then they applied them separately to the test set. Their results showed that the features group of candidate detector, contrast, texture, geometry, location, context, and patient information got AUCs of 85.8%, 78.7%, 71.8%, 75.3%, 68.6%, 81.6%, and 65.1%, respectively. While all the feature sets together obtained AUC of 90.6% against 92.0% in the case of CNN. In addition, a framework for CAD system utilizing CNN technique was presented in [6]. 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%.

5. 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.

Acknowledgments

This work was supported by the Center for Integrated Smart Sensors funded by the Ministry of Science, ICT & Future Planning as a Global Frontier Project (CISS- 2011–0031863). This work was also supported by International Collaborative Research and Development Programme (funded by the Ministry of Trade, Industry and Energy (MOTIE, Korea) (N0002252).

References

[1] R.L. Siegel, K.D. Miller, A. Jemal, Cancer statistics, 2016, CA Cancer J. Clin. 66 (1) (2016) 7–30.

[2] J. Virmani, N. Dey, V. Kumar, in: PCA-PNN and PCA-SVM Based CAD Systems For Breast Density Classification, Springer International Publishing, Warsaw, Poland, 2016, pp. 159–180.
[3] C. Muramatsu, T. Hara, T. Endo, H. Fujita, Breast mass classification on mammograms using radial local ternary patterns, Comput. Biol. Med. 72 (1) (2016) 43–53.
[4] H. Li, X. Meng, T. Wang, Y. Tang, Y. Yin, Breast masses in mammography classification with local contour features, BioMed. Eng. OnLine 16 (1) (2017) 44–54.
[5] S.A. Taghanaki, J. Kawahara, B. Miles, G. Hamarneh, Pareto-optimal multi-objective dimensionality reduction deep auto-encoder for mammography classification, Comput. Methods Progr. Biomed. 145 (2017) 85–93.
[6] Z. Jiao, X. Gao, Y. Wang, J. Li, A deep feature based framework for breast masses classification, Neurocomputing 197 (C) (2016) 221–231.
[7] J. Arevalo, F.A. González, R. Ramos-Pollán, J.L. Oliveira, M.A.G. Lopezd, Representation learning for mammography mass lesion classification with convolutional neural networks, Comput. Methods Progr. Biomed. 127 (2016) 248–257.
[8] N. Dhungel, G. Carneiro, A.P. Bradley, Automated mass detection in mammograms using cascaded deep learning and random forests, 2015 International Conference on Digital Image Computing: Techniques and Applications (DICTA), 2015.
[9] N. Dhungel, G. Carneiro, A.P. Bradley, A deep learning approach for the analysis of masses in mammograms with minimal user intervention, Med. Image Anal. 37 (2017) 114–128.
[10] T. Kooi, A. Gubern-Merida, J.-J. Mordang, R. Mann, R. Pijnappel, K. Schuur, A. d. Heeten, N. Karssemeije, A comparison between a deep convolutional neural network and radiologists for classifying regions of interest in mammography, International Workshop on Digital Mammography, 2016.
[11] M.A. Al-antari, M.A. Al-masni, S.U. Park, J.H. Park, Y.M. Kadah, S.M. Han, T.-S. Kim, Automatic computer-aided diagnosis of breast cancer in digital mammograms via deep belief network, Global Conference on Engineering and Applied Science (GCEAS), 2016.
[12] A.-B. Ayelet, L. Karlinsky, S. Alpert, S. Hasoul, R. Ben-Ari, 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.
[13] Y. Qiu, S. Yan, R.R. Gundreddy, Y. Wang, S. Cheng, H. Liu, B. Zheng, A new approach to develop computer-aided diagnosis scheme of breast mass classification using deep learning technology, J. X-Ray Sci. Technol. 25 (5) (2017) 751–763.
[14] G. Carneiro, J. Nascimento, A.P. Bradley, Automated analysis of unregistered multi-view mammograms with deep learning, IEEE Trans. Med. Imag. 36 (11) (2017) 2355–2365.
[15] J. Redmon, S. Divvala, R. Girshick, A. Farhadi, You only look once: unified, real–time object detection, IEEE Conference on Computer Vision and Pattern Recognition, 2016.
[16] M. Heath, K. Bowyer, D. Kopans, R. Moore, W.P. Kegelmeyer, The digital database for screening mammography, 5th international Workshop on Digital Mammography, 2000.
[17] M. Dong, X. Lu, Y. Ma, Y. Guo, Y. Ma, K. Wang, An efficient approach for automated mass segmentation and classification in mammograms, J. Digit. Imag. 28 (5) (2015) 613–625.
[18] T. Kooi, G. Litjens, B. v. Ginneken, A. Gubern-Mérida, C.I. Sánchez, R. Mann, A. d. Heeten, N. Karssemeijer, Large scale deep learning for computer aided detection of mammographic lesions, Med. Image Anal. 35 (2017) 303–312.
[19] H.R. Roth, L. Lu, J. Liu, J. Yao, A. Seff, K. Cherry, L. Kim, R.M. Summers, Improving computer-aided detection using convolutional neural networks and random view aggregation, IEEE Trans. Med. Imag. 35 (5) (2016) 1170–1181.
[20] T. Wu, R.H. Moore and D.B. Kopans, "Multi-threshold peripheral equalization method and apparatus for digital mammography and breast tomosynthesis," *U.S. Patent 7,764,820*, 2010.
[21] M.A. Al-antari, M.A. Al-masni, Y.M. Kadah, Hybrid model of computer-aided breast cancer diagnosis from digital mammograms, J. Scientific Eng. 04 (02) (2017) 114–126.
[22] M. Kallenberg, N. Karssemeijer, Comparison of tilt correction methods in full field digital mammograms, in: Digital Mammography/IWDM, Springer, Catalonia, Spain, 2010, pp. 191–196.
[23] M.A. Al-antari, M.A. Al-masni, S.U. Park, J.H. Park, M.K. Metwally, Y.M. Kadah, S.M. Han, T.-S. Kim, An automatic computer-aided diagnosis system for breast cancer in digital mammograms via deep belief network, J. Med. Biol. Eng. (2017). https://doi.org/10.1007/s40846-017-0321-6.
[24] A. Coates, A. Ng, H. Lee, An analysis of single-layer networks in unsupervised feature learning, Fourteenth International Conference on Artificial Intelligence and Statistics, 2011.
[25] M.A. Al-Masni, A.-A.A. Mugahed, J.M. Park, G. Gi, T.Y. Kim, P. Rivera, E. Valarezo, S.-M. Han, T.-S. Kim, Detection and classification of the breast abnormalities in digital mammograms via regional convolutional neural network, Engineering in Medicine and Biology Society (EMBC), 2017 39th Annual International Conference of the IEEE, 2017.
[26] M. Lin, Q. Chen and S. Yan, "Network in network," in *arXiv:*1312.4400, 2013.
[27] C. Cernazanu-Glavan, S. Holban, Segmentation of bone structure in X-ray images using convolutional neural network, Adv. Electr. Comput. Eng. 13 (1) (2013) 87–94.
[28] D. Scherer, A. Müller, S. Behnke, Evaluation of pooling operations in convolutional architectures for object recognition, Artificial Neural Networks–ICANN, 2010.
[29] Q. Guo, F. Wang, J. Lei, D. Tu, G. Li, Convolutional feature learning and Hybrid CNN-HMM for scene number recognition, Neurocomputing 184 (2016) 78–90.
[30] J.H. Park, S.U. Park, M. Zia Uddin, M. Al-antari, M. Al-masni, T.-S. Kim, A single depth sensor based human activity recognition via convolutional neural network, 4th World Conference on Applied Sciences, Engineering & Technology, 2016.
[31] J. Redmon, "Open source neural networks in c," http://pjreddie.com/darknet/, 2013-2016.
[32] E. Szymańska, E. Saccenti, A.K. Smilde, J.A. Westerhuis, Double-check: validation of diagnostic statistics for PLS-DA models in metabolomics studies, Metabolomics 8 (1) (2012) 3–16.
[33] Y. Bar, I. Diamant, L. Wolf, S. Lieberman, E. Konen, H. Greenspan, Chest pathology identification using deep feature selection with non-medical training, Comput. Methods Biomech. Biomed. Eng. 13 (2016) 1–5.
[34] R.K. Samala, H. Chan, L. Hadjiiski, M.A. Helvie, J. Wei, K. Cha, Mass detection in digital breast tomosynthesis: Deep convolutional neural network with transfer learning from mammography, Med. Phys. 43 (12) (2016) 6654–6666.
[35] J. Yosinski, J. Clune, Y. Bengio, H. Lipson, How transferable are features in deep neural networks? Advances in Neural Information Processing Systems, 2014.
[36] O. Russakovsky, J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein, A.C. Berg, L. Fei-Fei, ImageNet large scale visual recognition challenge, Int. J. Comput. Vis. 115 (3) (2015) 211–252.
[37] C.E. Metz, Receiver operating characteristic analysis: a tool for the quantitative evaluation of observer performance and imaging systems, J. Am. College. Radiol. 3 (6) (2006) 413–422.
[38] D.P. Chakraborty, K.S. Berbaum, Observer studies involving detection and localization: modeling, analysis, and validation, Med. Phys. 31 (8) (2004) 2313–2330.