International Journal of Computing and Artificial Intelligence

E-ISSN: 2707-658X
P-ISSN: 2707-6571
www.computersciencejournals.com/ijcai
IJCAI 2025; 6(1): 137-140
Received: 06-02-2025
Accepted: 15-03-2025

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Classification of mammographic abnormalities using convolutional neural networks

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DOI: https://www.doi.org/10.33545/27076571.2025.v6.i1b.143

Abstract
Distinguishing between benign and malignant mammography images is a complex task even for experimented radiologists and, to deal with this issue, researchers developed computer-aided diagnosis systems. This study introduces a machine learning model to classify mammography images into benign and malignant classes. We extract region of interests using the appropriate mask for each mammography image, and we feed it into a modified LeNet model. We add two parallel convolutional blocks to the original LeNet architecture, and we notice a significant increase in the performance. We pre-train the model on the DMID dataset and a subset of the BCDR dataset, and we test it on the remaining subset. The modified lightweight model reached an accuracy of 99%.

Keywords: Breast cancer, mammography, LeNet, deep learning, convolutional neural networks

Introduction

According to [1], cancer is a leading cause of death around the world, and it is estimated that there will be 2.5 million deaths in the next 20 years. Since the inception of deep learning techniques, scientist has been focusing on applying this knowledge in medical image processing in order to diagnose and eventually cure diseases.

This study introduces a novel machine learning algorithm to classify mammography image into benign and malignant classes. The computer-aided diagnosis (CADx) system consists of region of interest (ROI) extraction and classification. As a feature extractor and classifier, we use a modified lightweight LeNet model. By adding a convolutional layer and fusing the features of the second and third blocks, the network manages to learn robust feature that are fed into a fully connected network with two output neurons and a softmax activation function. We compare the proposed model with the original LeNet model in terms of accuracy, precison and recall and we notice that the modified LeNet outperforms the original model.

Oza *et al.* [2] used test time augmentation to eveluate the results of deep learning classifier that consists of CNNs that uses transfer learning. Ahmed *et al.* [3] used a EfficientNet model to extract features from mammography images and Mixture of Experts (MoEs) where each expert is used to process a subset of the latent space vector. The classification is performed using an advanced gating network that adjust how much influence each expert has on the final output. Karagoz *et al.* [4] introduced a hybrid deep learning model that consists of two phases i.e. feature extraction using variational autoencoders and classification using 1D CNNs. Four encoders are employed to extract features from diffrent mammography views, then, the resulting feature vectors are aggregated before feeding the resulting tensor to the deep learning classifier. Isosalo *et al.* [5] used pretrained convolutional neural netwroks i.e. ResNet22 to extract features from different mammography view i.e. L-CC, R-CC, L-MLO, and R-MLO. The set of features are fused then fed into a softmax classifier that will predict the diagnosis for a certain patient. Cantone *et al.* [6] compared the performance of 33 deep learning models inclusing CNN and transformers based models in classifying mammography images at different resolutions. The study concluded that the efficientNet yield the best accuracy with 1536×768 input resolution.

Datasets

The digital mammography dataset for breast cancer diagnosis and research (DMID) dataset [7] contains 510 mammography images of size 4751×6000 and belonging to 3 classes i.e.

normal, benign, and malignant. Each abnormal image is accompanied with its binary mask. During this study, we select the abnormal cases from the DMID dataset.
The Breast Cancer Digital Repository (BCDR) [8] dataset is composed of 727 patient cases including CC and MLO views. The mammography images are 3328 × 4084 in size. The images are available in TIFF format.

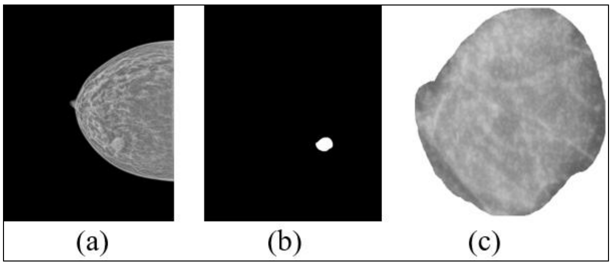

Fig 1: (a) is a mammography image. (b) is its mass segmentation mask. And (c) is the cropped region of interest.

Convolutional Neural Networks

Convolutional neural networks (CNNs) [9] are inspired by the human visual cortex and they consists of convolutional layers, batch normalization layers [10], and pooling layers [11]. CNNs learns features by itself via filter optimization. CNNs are not invariant to translation since they apply downsampling operations to the input image [12].
LeNet [13] is a set of CNNs created in the 90's. LeNet-5 is one of the first convolutional neural networks and it has a significant impact on the history of computer vision and artificial intelligence in general. The LeNet-5 model is composed of two convolutional layers each one is succeeded by a batch normalization layer, a rectified linear unit (ReLU) activation function, and a max pooling layer.

Materials and Methods

In this study, we propose a deep learning [14] architecture to classify ROI extracted from mammography images into benign and malignant cases. First, we add a parallel branch to the second convolutional block. Although, it has the same output shape, we substitute the max pooling layer with a min pooling layer, and we fuse the features of the two branches before feeding the output to the third convolutional block. By applying this method, we allow the network to learn robust features and, thus, to converge to a better solution. A second improvement is within the activation function, the ReLU activation function had been widely used in CNNs, but it suffers from the vanishing gradient problem. To deal with this issue, we use the exponential linear unit (ELU) [15] which avoids the vanishing gradient problem by having negative values. The proposed network has two output neurons and a log softmax activation function. (see Figure 2).
We trained the proposed network on the DMID and a subset of the BCDR datasets using the cross entropy loss function and an adam optimizer with 1e-4 learning rate.

Results and Findings

We use the Pytorch python library to implement the modified LeNet model, and we compare its performance with a standard LeNet-5 model.
Table 1 shows the recorded metrics using the LeNet-5 and the modified LeNet models. The proposed model outperformed the LeNet-5 model while scoring 99% accuracy on the BCDR test set.

Table 1 : The recorded results using the proposed LeNet model

Method	Accuracy	Precision	Recall	F1-score
LeNet	0.96	0.96	0.96	0.96
Modified-LeNet	0.99	0.99	0.98	0.99

Figure 3 shows the confusion matrices of the LeNet-5 and the modified LeNet model. For instance, our proposed model manages to classify all the malignant cases correctly and only 2 benign images are misclassified as malignant. On the other hand, the LeNet-5 model has a false positive value equal to 2, which means that 2 malignant images are misclassified by the network, and a false negative value equal to 3.

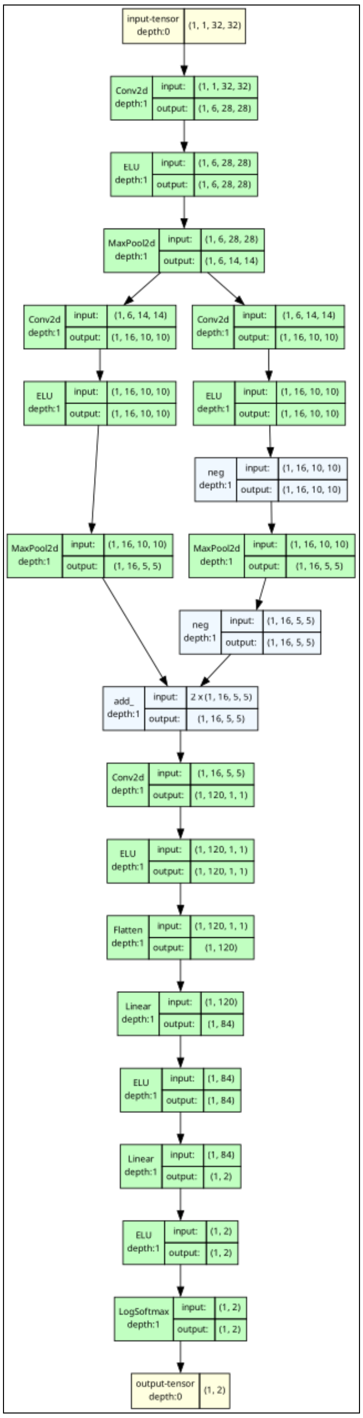

Fig 2 : The proposed modified LeNet model

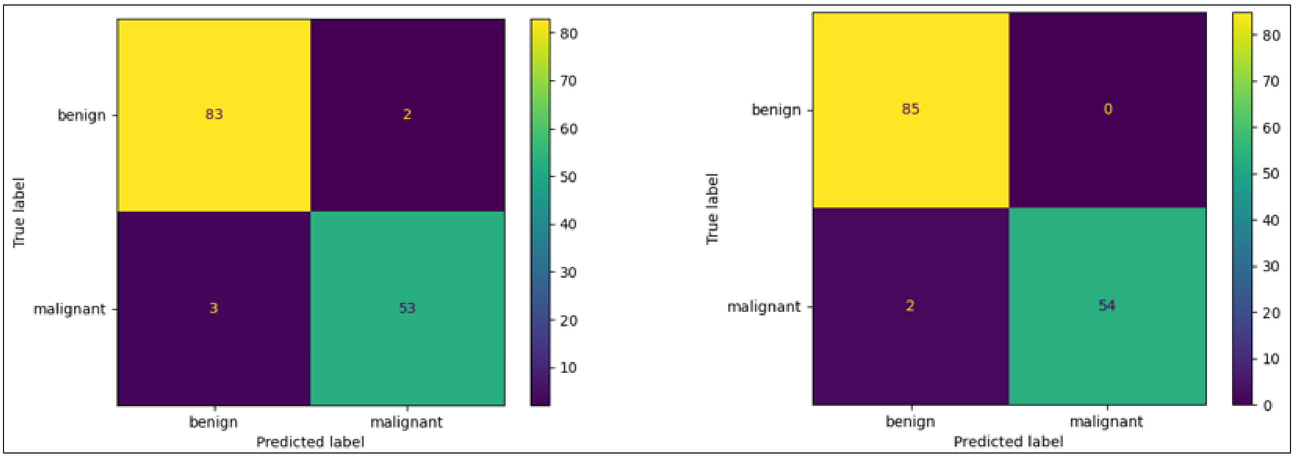

Fig 3 : The confusion matrices of the LeNet-5 model and our proposed model

Figure 4 shows the ROC curves of the proposed and the baseline models. Although both of the models show a good specifity and sensitivity, the modified LeNet has a slight improvement in terms of true and false positive rates.

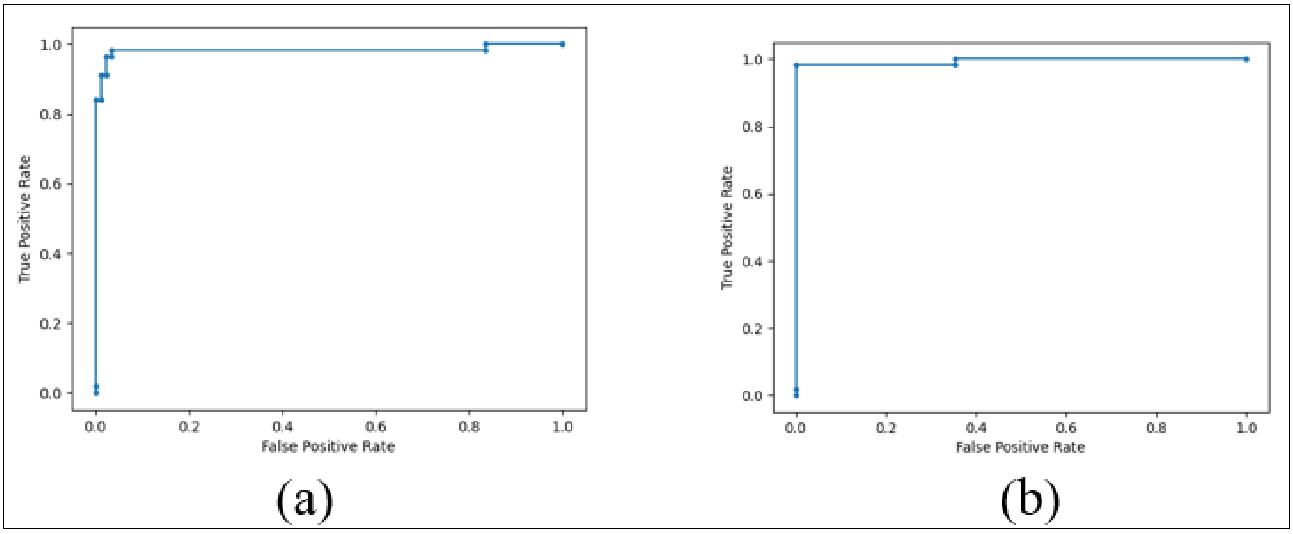

Fig 4: (a) is the ROC curve of the original LeNet-5 model. (b) is the ROC curve of the modified LeNet model

Conclusion

This study introduced a novel deep learning architecture based on the LeNet-5 model. The model outperformed the baseline model while reaching an accuracy of 99%. The proposed LeNet model has a lightweight architecture which allows it to execute fast with few parameters. The idea of fusing parallel branches has shown good performance with the LeNet model but in some cases a deeper architecture is needed in order to learn more robust features. In further studies, we propose applying the same methodology to other state-of-the-art CNNs such as the AlexNet.

Acknowledgments

During this study, we used the computation resources provided by the department of computer science at Aberystwyth University.

References

1. Organization WH. Online; https://www.who.int/news-room/factsheets/detail/cancer.
2. Oza P, Sharma P, Patel S. Breast lesion classification from mammograms using deep neural network and test-time augmentation. Neural Computing & Applications. 2024 FEB;36(4):2101-2117.
3. [3] Ahmed HOA, Nandi AK. High Performance Breast Cancer Diagnosis From Mammograms Using Mixture of Experts With EfficientNet Features (MoEffNet). IEEE ACCESS. 2024;12:133703-13325.
4. Karagoz MA, Nalbantoglu OU, Karaboga D, Akay B, Basturk A, Ulutabanca H, *et al*. Deep learning-based breast cancer diagnosis with multiview of mammography screening to reduce false positive recall rate. Turkish journal of electrical engineering and computer sciences. 2024, 32(3).
5. [5] Isosalo A, Inkinen SI, Turunen T, Ipatti PS, Reponen J, Nieminen MT. Independent evaluation of a multi-view multi-task convolutional neural network breast cancer classification model using Finnish mammography data. Computers in biology and medicine. 2023 JUL, 161.
6. Cantone M, Marrocco C, Tortorella F, Bria A. Convolutional Networks and Transformers for Mammography Classification: An Experimental Study. SENSORS. 2023 Feb, 23(3).
7. Oza P, Oza U, Oza R, Sharma P, Patel S, Kumar P, *et al*. Digital mammography dataset for breast cancer

diagnosis research (DMID) with breast mass segmentation analysis. Biomedical Engineering Letters. 2024;14(2):317-330.
8. Repository BCD. Online;. http://bcdr.inegi.up.pt.
9. O'shea K, Nash R. An introduction to convolutional neural networks. arXiv preprint arXiv:151108458. 2015.
10. Bjorck N, Gomes CP, Selman B, Weinberger KQ. Understanding batch normalization. Advances in neural information processing systems. 2018, 31.
11. Graham B. Fractional max-pooling. arXiv preprint arXiv:14126071. 2014.
12. Long J, Shelhamer E, Darrell T. Fully Convolutional Networks for Semantic Segmentation. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR); c2015.
13. LeCun Y, Bottou L, Bengio Y, Haffner P. Gradient-based learning applied to document recognition. Proceedings of the IEEE. 1998;86(11):2278-2324.
14. LeCun Y, Bengio Y, Hinton G. Deep learning. nature. 2015;521(7553):436-444.
15. Clevert DA, Unterthiner T, Hochreiter S. Fast and accurate deep network.