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HYBRID CONVOLUTION NETWORK FOR MEDICAL IMAGES PROCESSING AND BREAST CANCER DETECTION

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Abstract. In this paper, the breast cancer detection problem using convolutional neural networks (CNN) is considered. The review of known works in this field is presented and analysed. Most of them rely only on feature extraction after the convolutions and use the precision of classification of malignant tumors as the main criterion. However, because of the huge number of parameters in the models, the time of computation is very large. A new structure of CNN is developed — a hybrid convolutional network consisting of convolutional encoder for features extraction and reduction of the complexity of the model and CNN for classification of tumors. As a result, it prevented overfitting the model and reduced training time. Further, while evaluating the performance of the convolutional model, it was suggested to consider recall and precision criteria instead of only accuracy like other works. The investigations of the suggested hybrid CNN were performed and compared with known results. After experiments, it was established the proposed hybrid convolutional network has shown high performance with sensitivity, precision, and accuracy of 93,50%, 91,60%, and 93%, respectively, and requires much less training time in the problem of breast cancer detection as compared with known works.

Keywords: breast cancer detection, hybrid convolutional network, encoder, classification sensitivity, dimensionality reduction.

INTRODUCTION

Breast cancer is a very common cancer among women between the ages of 35 and 55 [1]. Diagnosing breast cancer is frequently discussed as a classification problem within neural networks. Detecting and diagnosing breast cancer in early stages is critical in saving women's lives. Detecting this cancer in its early stages can help prevent the spread of cancer to other organs/tissues allowing doctors to help the patient before it is too late. Early detection requires methods that are systematic and dependable, allowing healthcare professionals to accurately distinguish between benign and malignant tumors [2]. For these reasons, the exact detection and classification of breast tumors is extremely important for public health and to the lives of cancer patients [3].

There are four types of breast cancer: in situ, invasive ductal carcinoma, inflammatory breast cancer, and metastatic cancer [4]. Breast cancer detection is important in developing countries, where the number of patients is dramatically higher. Moreover, detecting breast cancer is a challenging and time-consuming task requiring doctors to manually label scans. Although, there are supervised and unsupervised machine learning algorithms that assist doctors. According to the World Health Organization (WHO) [5], a mammography scan is more efficient and cost-effective for breast cancer detection. Although it is more expensive than other medical images, the quality of the image is superior to other medical scans and therefore mammography scans, from the BreakHis dataset [6] have been used in this work.

The main goal of this work is the development and investigation of hybrid convolutional network to increase the sensitivity and to reduce the complexity of the model for breast cancer detection. A convolutional autoencoder was proposed to extremely decrease the computation time.

REVIEW OF PREVIOUS WORKS

There are a lot of studies that consider breast cancer detection using CNNs. However, most of them rely on the accuracy in their experiments, but accuracy in any cancer detection is not the only valid factor that should be considered [7]. In these tasks, the sensitivity of models should be considered to understand how many times the model misclassified cancer. Authors in [8] proposed a state-of-the-art convolutional neural network (DenseNet) for breast cancer detection using Breast Cancer Histology images (BACH) with an accuracy of 85,6%. The misclassification rate for cancer class was 14,4% on average. In their work, the sensitivity (on average for 4 classes) of ResNet 50 was compared with their proposed CNN at 76% and 79% respectively.

Compared with pre-existing CNN models (VGG-16, VGG19, Xception, Resnet, Inception) with 80% accuracy in multiclass classification, authors in [9] proposed a model where the accuracy was 83,97% on average for two classes (Benign and Malignant). The proposed model was a combination of Inception and Resnet using the BreakHis data set, which contains 7909 mammography scans with four magnification factors (40X, 100X, 200X and 400X).

In [10], it was stated that because of the architecture of DenseNet, in which all layers are fully connected to every previous layer, and with a short connection between those layers near the input and output, the model could be trained more efficiently and accurately.

In [11] a DenseNet network authors proposed model which achieved high processing performances with 95,4% of accuracy. The Authors claim they first used weights from Imagenet and fine-tuned the model to train DenseNet. All convolutional parts of the network were frozen but the fully connected layer was trainable. Authors in [12] used an atrous DenseNet that achieves multi-scale feature extraction by integrating the atrous convolutions to the dense block. The authors in [12] compared two datasets, BACH and CCG, in which the average class accuracy for the proposed model was 82,50% and 87,05% respectively for each dataset.

A new model of convolutional neural network was proposed in [13], where the authors used 400 images with 40x magnification for training data and 200 for validation data. In [13] three different ConvNet architectures were evaluated: 1) a 3-layer ConvNet architecture, 2) a 4-layer ConvNet architecture, and 3) a deeper

6-layer ConvNet architecture. The 3-layer ConvNet included one convolution, one pooling and one fully connected layer. The 4-layer had two convolutional and two pooling layers and the last layer was fully connected. The 6-layer ConvNet architecture comprises four convolutional and pooling layers with 16 units, a fully connected layer. According to the results in [13], deep architectures shows better result with 1,06% accuracy.

Authors in [14] proposed semi-supervised learning (SSL) using convolutional neural networks. The accuracy of the developed model was 82,43% and the area under the curve (AUC) observed in their study was 88,18%. There were 1874 pairs of mammogram images used during the experiments. Moreover, the authors developed three data weighing equations using exponential function, Gaussian function, and Laplacian function. Based on results [14], comparing two other weighting equation, the exponential function has shown better results with 82,43%, 81,00% and 72,26% for labelling accuracy, sensitivity and specificity respectively.

In [16] authors applied Principal component analysis (PCA) for Hybrid Fuzzy CNN Network. The idea of using PCA was to reduce the number of extracted features. In their work, the authors proposed a model where CNN VGG 16 was used for feature extraction and FNN NEFClass was used for image classification.

DATASET

The open source BreakHis dataset was used during the experiment. The dataset includes two classes benign and malignant tumors. The dataset is also separated into four magnification zooms 40X, 100X, 200X and 400X; 5000 images were used for training and 350 images were used for testing. Fig. 1 illustrates some input images that were used for training the model. Fig. 1, *a–d* belong to the benign category and Fig. 1, *e–h* belong to the malignant category.

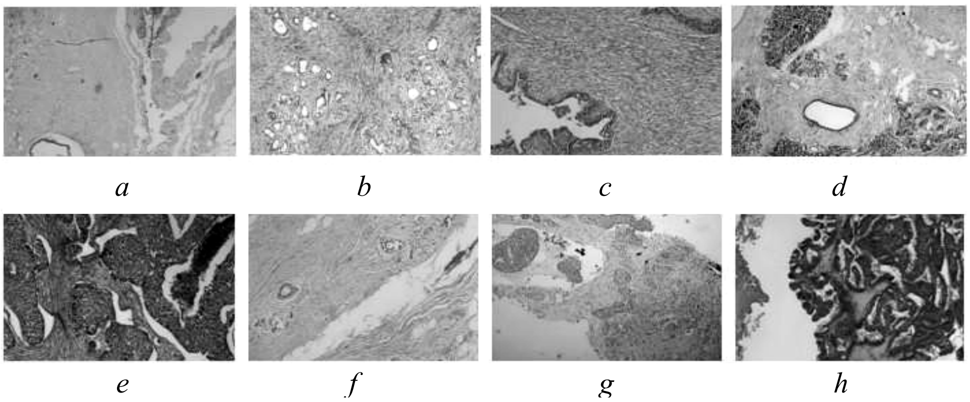

Fig. 1. Sample of input images: *a* — adenosis; *b* — fibroadenoma; *c* — phyllodes_tumor; *d* — Tubular_adenoma; *e* — Ductal_carcioma; *f* —Lobular_ carcioma; *g* — Muconous carcinoma; *h* — Papillary carcioma

ARCHITECTURE AND TRAINING OF CONVOLUTIONAL AUTOENCODER

The aim of the autoencoder is to learn a compressed distributed representation for the given data typically for the purpose of dimensionality reduction. On the other hand, there is a principal component analysis (PCA) for the same task (reduction dimensionality). However, there are some advantages [17] of using autoencoder like: 1) autoencoder can represent both linear and non-linear transformations in encoding but PCA can perform only linear transformations; 2) it could be more efficient in terms of model parameters to learn several layers with an autoencoder rather than one massive transformation with PCA; 3) it gives a representation as the output of each layer and having multiple representation of different dimensions is more practical.

One of the reasons a convolutional autoencoder was used during experiments is because it is very challenging to find significantly sized datasets with labels and autoencoder is an unsupervised model that does not require the dataset to be labelled. Another advantage of the autoencoder is that it makes the model smaller. Respectively, the model would have less parameters and as a result, the time of computation and training will drastically decrease. For example, in Dense Net there are a total of 58,420,802 parameters and 7,037,504 of them are not trainable. However, in the proposed convolutional autoencoder there are 2,940,865 parameters and only 3,840 of them are non-trainable.

Fig. 2 illustrates the architecture of an autoencoder. In the autoencoder there are layers between the input and output and the sizes of these layers are smaller than the input layer. For example, the input vector has a dimensionality of N which means that the output will also have a dimensionality of N. The input goes through a layer of size P, where the value of P is less than N. The autoencoder receives unlabelled input which is then encoded to reconstruct input. The important part of autoencoder is the Bottleneck approach for representation learning.

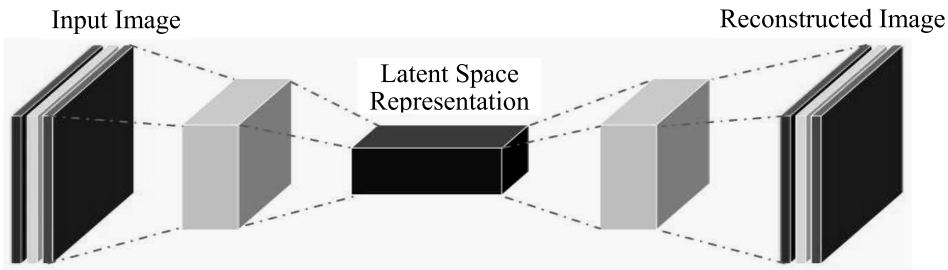

Fig. 2. The architecture of an autoencoder

In the current work, several architectures of convolutional autoencoder were used during the experiment. The convolutional autoencoder was modified with 18 encoding layers and 14 decoding layers. There were eight convolutional and two max pooling layers in encoder. In decoder there were six convolutional and two upsampling layers. Batch normalization was used between each convolutional layer. The proposed convolutional autoencoder was trained in a way, that the model would extract informative features (Codes) during the encoding process, and the decoder could then reconstruct the original input image of the encoder. The model could recreate the original image, even though some noises were applied to the scans. A comparison of the input images and reconstructed images is shown in Fig. 3. After creating a successful autoencoder-model, the output of the encoder will be used with a fully connected layer to create a full model (Convolutional Autoencoder).

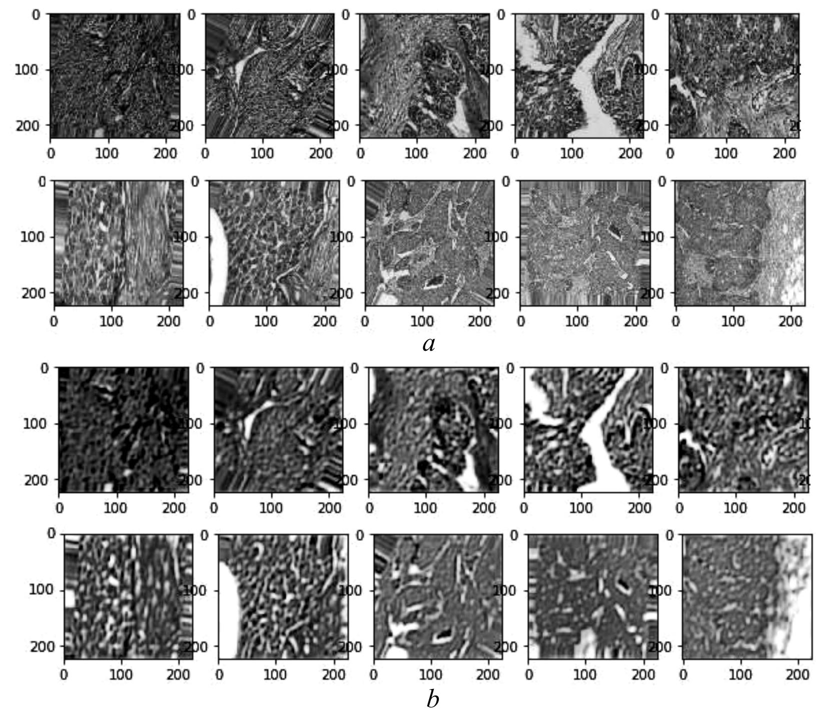

Fig. 3. On scans (*a*) noises were added, and scans (*b*) are reconstructed to original test data

The accuracy of the recreated test data for convolutional autoencoder was 79,38%.

EXPERIMENTAL INVESTIGATIONS AND ANALYSIS

For training an autoencoder there are four parameters that it is needed to be set. The first one is code size. The code size represents the number of nodes in the middle layer and smaller size results in more compression. The second parameter is the number of layers and the autoencoder could be as deep as we want it to be. Another parameter is the loss function. The last parameter is the number of nodes per layer. The number of nodes per layer decreases with each subsequent layer of the encoder and increases back in the decoder. Also, the decoder is symmetric to the encoder in terms of layer structure.

The Adam optimizer with learning rate 0,001 was used for training Dense-Net whereas, in convolutional autoencoder the RMSprop ($lr = 0{,}001$) has shown better results.

All scans were pre-processed, before being used to train the model by resizing, normalizing and dimensionality reduction methods. In this paper, all experiments were developed using Jupyter Labs, Tensorflow 2 and Python 3. The programs were implemented on a virtual machine with an NVIDIA Tesla GPU and eight Intel CPUs.

Fig. 4, *a* and *b* illustrate how the loss for training and validation data was changed. Multiple tests were done using different numbers of epochs. It was found that 250 epochs provided better results compared to larger number of epochs like 500. The more epochs, the more chance the model will have overfitting. According to Fig. 6, it is better to use learning rate 0,001 for the current model. However, this parameter could be different for other models.

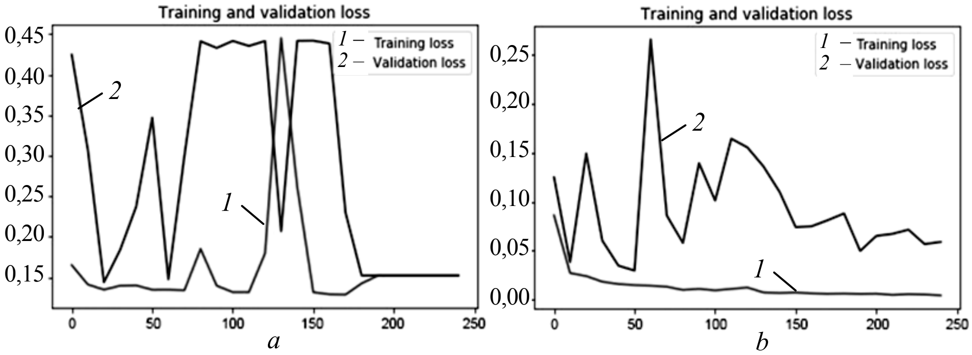

Fig. 4. Loss comparison for training and validation data with learning rate 0,01 and 0,001 on (*a*) and (*b*) respectively

In previous work [17], a modified Inception V3 was proposed for breast cancer detection. In this work a hybrid convolutional network was proposed using a fine-tuned DenseNet121 and modified convolutional autoencoder. In the proposed hybrid convolutional network, the convolutional autoencoder was used as a feature extraction and the DenseNet was used as a classifier. Fig. 5 demonstrates the architecture of the proposed model.

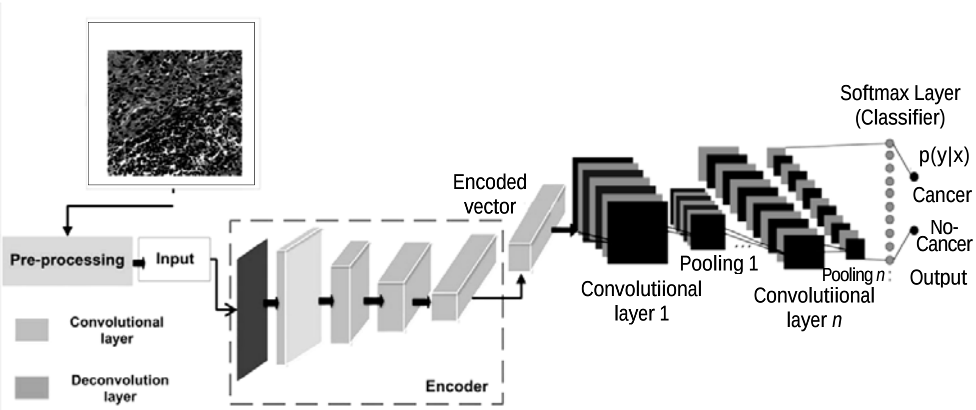

Fig. 5. Modified architecture of hybrid convolutional network

Table 1 shows the result of the proposed model for each class.

Table 1. The results of breast cancer recognition using a convolutional autoencoder

Class	Precision, %	Recall, %	F1-Score, %	Support
Class 0	90	95	93	747
Class 1	95	90	92	1626
Weighted ayg	93,2	93,5	93,3	2373

The experiment proves that it is not necessary to have large data sets to train a convolutional autoencoder from scratch. Comparatively, training the DenseNet and Inception-v3 convolutional networks from scratch, require a large number of input images. Thus, the convolutional autoencoder has a simplified model, and training time is significantly reduced compared to DenseNet or Inception-v3. Fig. 6 illustrates the performance of the model with different number of input data as training data.

Also, the appearance and image quality of the input data significantly affect the performance of the model. BreakHis and Breast histology datasets were used for comparison. In the table 2 shows the performance of the model with different input data.

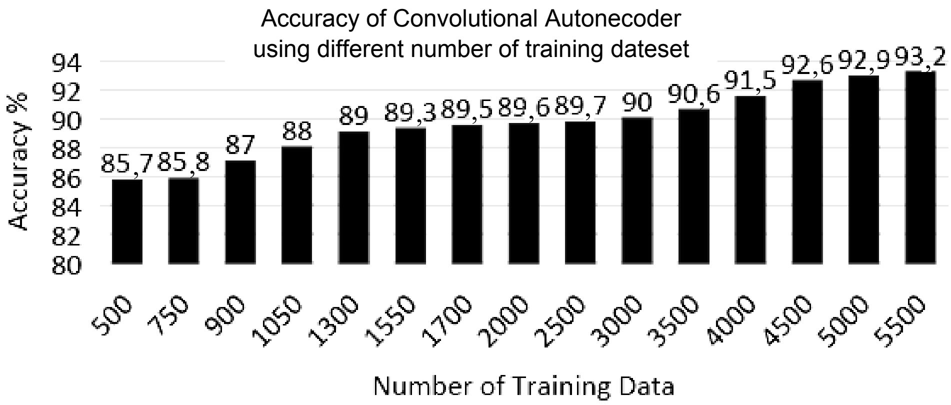

Fig. 6. Accuracy of proposed model for different size of data sets

Table 2. Comparison of the quality of the model of the convolutional autoencoder for different datasets

Factors/Datasets	**BreakHis,** %	**Breast histology,** %
Accuracy	93	90,5
Precision	93,2	91,6
Recall	93,5	92,40
F1-Score	93,3	92

Table 3 shows three different deep convolutional networks that were used for the current task. According to table 3, the hybrid convolutional network has shown better results as compared to other methods, the training time was lower. There are plenty of studies for breast cancer detection using deep learning, and most of them rely only on accuracy. However, sensitivity (recall) is the most important factor that should be kept in mind while training deep neural networks. With recall it is possible to assess whether the network predicts cancer as a cancer, so in the current work both recall and precision of the model were considered.

Table 3. Result of comparison different models for detecting breast

CNN models	**Factors**			
	Precision, %	Recall, %	F1 score, %	Training Time
Modified Inception V3 [17]	66,66	85,70	74,99	27h
DenseNet 121	75,73	86,1	80,84	24h
Hybrid convolutional neural network	91,60	93,50	92,5	13h

Based on the data from table 3 and table 1, it can be concluded that the sensitivity of the model (recall) when using a convolutional autoencoder gives a better result compared to Inception-v3. It should also be noted that only 5% of class 0 (cancer), was misclassified.

CONCLUSION

1. In this paper, a hybrid convolutional neural network was developed, and investigated in the problem of breast cancer detection. In the proposed hybrid convolutional network the convolutional autoencoder was used as a feature extraction while CNN DenseNet was used as a classifier.

2. In the experiments it was determined that sensitivity, precision and accuracy of the proposed model were 93,50%, 91,60% and 93% respectively. The comparison with known CNN was performed which has shown the proposed hybrid CNN has higher sensitivity (recall) than known CNN models.

3. Besides the hybrid CNN has fewer parameters compared to DenseNet, as a result, the model is less complex and prevents overfitting. Moreover, the used autoencoder is an unsupervised model and does not require labeled data.

4. In addition, during the experiments it was established that hybrid CNN requires less training time as compared with known CNN models.

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INFORMATION ON THE ARTICLE

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ГІБРИДНА ЗГОРТКОВА МЕРЕЖА ДЛЯ ОБРОБЛЕННЯ МЕДИЧНИХ ЗОБРАЖЕНЬ ТА ВИЯВЛЕННЯ РАКУ МОЛОЧНОЇ ЗАЛОЗИ / Ю.П. Зайченко, М. Надеран, Г. Гамідов

Анотація. Розглянуто проблему виявлення раку молочної залози з використанням згорткових нейронних мереж (ЗНМ). Наведено огляд та аналіз праць з цієї галузі. Зазначається, що більшість з них засновано на вилученні ознак у результаті згортки з використанням як основного критерію точність класифікації пухлин. Унаслідок великого обсягу параметрів, що оптимізуються, час навчання дуже тривалий. Розроблено нову структуру ЗНМ — гібридну мережу, що складається з енкодера для отримання первинних ознак і скорочення розмірності моделі та декількох шарів згортки для класифікації пухлин. Це дало змогу запобігти перенавченню мережі та скоротити час навчання. Для оцінювання якості класифікації запропоновано використовувати критерій чутливості (до злоякісних пухлин) разом із критерієм точності на відміну від відомих праць. Це дозволило скоротити відсоток пропуску злоякісних пухлин. Проведено експериментальні дослідження розробленої гібридної згорткової мережі та порівняно з іншими працями. Установлено, що гібридна ЗНМ має високі показники якості класифікації, а також чутливість до ракових пухлин і точність класифікації 93,50%, 91,60% відповідно і потребує значно менше часу на навчання класифікації пухлин молочної залози порівняно з відомими працями.

Ключові слова: виявлення раку молочної залози, гібридна згорткова мережа, кодер, чутливість класифікації, зменшення розмірності.