# Computer-Aided Diagnosis System with Backpropagation Artificial Neural Network—Improving Human Readers Performance

**Sławomir Stemplewski and Marek Polewski**

**Abstract** This article presents the results of a study into possibility of artificial neural networks (ANNs) to classify cancer changes in mammographic images. Today's Computer-Aided Detection (CAD) systems cannot detect 100 % of pathological changes. One of the properties of an ANN is generalized information —it can identify not only learned data but also data that is similar to training set. The combination of CAD and ANN could give better result and help radiologists to take the right decision.

**Keywords** Computer-aided detection · Artificial neural networks · Mammographic images

## 1 Introduction

Mammographic interpretation is one of the most difficult tasks in all of radiology. Breast parenchyma patterns are not stable from year to year even within the same patient or indeed the same breast [1]. Breast cancers have variable appearance in mammograms—from obvious masses to very small asymmetries. Many images require interpretation by more than one radiologist. This is hard to implement because of number of women in the population for whom yearly screening mammography is recommended. Only in the United States of America each year, approximately 350,000 persons are diagnosed with breast, cervical, or colorectal cancer, and nearly 100,000 die from these diseases. The large number of images which individual radiologists are required to evaluate leads to fatigue and high error-rates. Given these difficulties approximately 20 % of cancers are known to be

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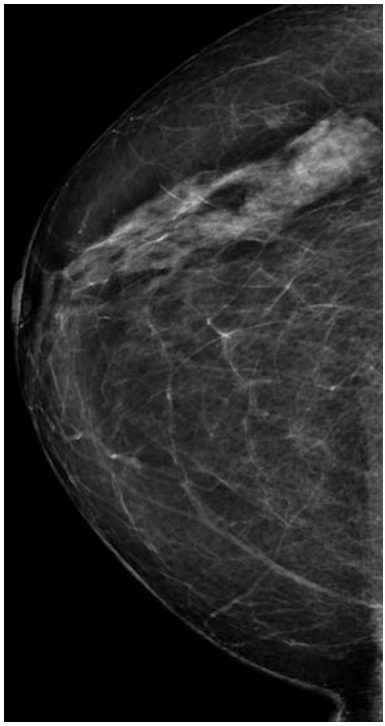

**Fig. 1** Mammographic image

missed by mammography. One of the causes is the reduced sensitivity of mammography in the detection of lesions in dense breast tissues. But even in images with visible lesions, the combinations of the variable presentation of breast cancer on mammograms makes it hard for the radiologist to take the right decision. Accuracy of mammographic interpretation depends on many factors. A good computer analyzer to help the radiologist in this difficult task would therefore be a desirable tool (Fig. 1).

## 2 Computer-Aided Detection

Computer-Aided Detection (CAD) is a tool developed to help radiologists with mammographic interpretation. The technology is designed to increase observational accuracy. It is based on procedures in medicine that assist doctors in the interpretation of medical images. CAD systems are able to scan digital images (e.g. mammographic images) and search for typical appearances of suspicious sections. If the system finds a place with lesions then the relevant part of image is highlighted. CAD systems described in the literature are based on a variety of models and exhibit a variety of behaviours, which makes them hard to compare. Scientist

have to remember that results from studies were performed in an artificial study environment—readers perform at a different level than they would normally. Results from such retrospective artificial environment studies may not have much bearing on the true clinical performance the systems in question. Performance in a realistic setting is hard to measure, as the incidence of cancer is low in the typical screening population.

Digital images are prepared and analyzed in several steps [2]:

- The image is preprocessed to reduce artifacts and image noise and to filter our unwanted details.
- The image is segmented to reveal various structures in the image.
- Every detected region is analyzed individually for special characteristics such as compactness, form, size and location.
- Having obtained the regions of interest, each one is evaluated individually for the probability of a true positive (TP). The system uses such procedure as the nearest-neighbor rule, minimum distance classifier, Bayesian classifier, cascade classifier, artificial neural network radial basic function network (RBF), and SVM.

Detected structures are highlighted in the image for the radiologist if they have reached a certain threshold level. Today's CAD systems cannot detect 100 % of pathological changes. The hit rate can reach up to 90 % depending on the application and system. Positive results returned by the system are divided into two classes: true positive—those corresponding to genuine pathological features—and false-positive—those produced by healthy tissue sections.

## 3 Artificial Neural Network

Artificial neural networks have been successfully applied to the identification of complex nonlinear system for many years [3, 4]. For most problems, neural networks require a large number of input neurons and necessitate a long computation time. In recent years computing power has increased significantly. That has created new opportunities for ANNs. In this study, the authors decided to use backpropagation as the training method and the hyperbolic tangent as the activation function:

$$f(x) = \frac{1}{1 + e^{-\beta x}} - 1. \tag{1}$$

This is a bipolar sigmoid function, which range from −1 to 1. It should be noted that the error is computed using the derivative of the activation function described by the formula:

$$f'(x) = 1 - a^2, \tag{2}$$

where $a$ is the function of activation (1).

One of the key properties of artificial neural networks is their ability to generalize from data. Unfortunately, however, in the present example, the straightforward application of backpropagation was found to lead to overfitting of data. To solve this problem, the data was subject to a preprocessing phase involving the addition of random noise. In addition, to prevent rate learning, the order of examples in the training set was randomized. This sample modification was found to yield greatly improved performance.

## 4 Network Learning and Testing Process

This work used a multi-layered back-propagation network trained using supervised learning. That process requires supplying network with learning samples of all the kinds of data it should be able to recognize. Samples of the abnormal and healthy tissue are presented in Figs. 2 and 3. Prepared samples were segregated into two sets; the first was used in the learning process, and the second to verify network responses. Each sample was later translated into multiple equi-sized and overlapping smaller parts. The network is initialized with N * N + 1 inputs, where N is the

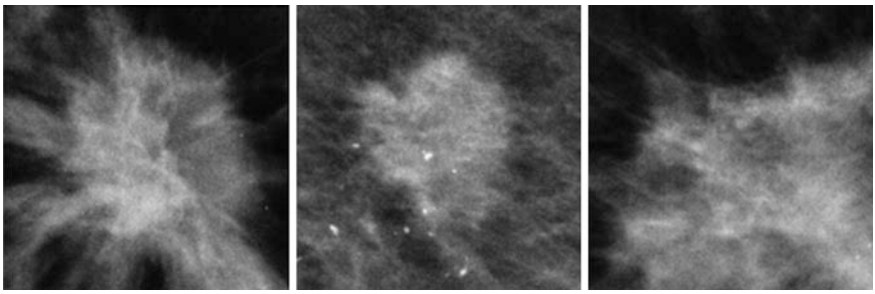

**Fig. 2** Pathological tissue samples

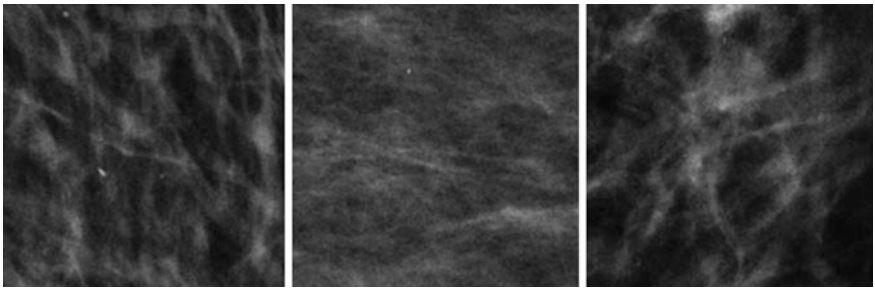

**Fig. 3** Normal tissue samples

**Table 1** Healthy samples set test results

| | Best match | Second best | Third best | Conclusion |
|---|---|---|---|---|
| 1 | Healthy | Healthy | Healthy | Healthy |
| 2 | Healthy | Healthy | Healthy | Healthy |
| 3 | Healthy | Healthy | Healthy | Healthy |
| 4 | Healthy | Healthy | Healthy | Healthy |
| 5 | Healthy | Healthy | Healthy | Healthy |
| 6 | Healthy | Healthy | Sick | Healthy |
| 7 | Healthy | Healthy | Healthy | Healthy |
| 8 | Healthy | Healthy | Sick | Healthy |
| 9 | Healthy | Healthy | Healthy | Healthy |
| 10 | Healthy | Healthy | Healthy | Healthy |
| 11 | Healthy | Healthy | Healthy | Healthy |

border size of the generated sample parts. Each input is set with pixel value scaled to a number between 0 and 1. The number of network outputs equals the size of the training set. Later the network will be able to show which samples are closest to the evaluated chunk. This allows us to easily add new learning samples aimed at specific network flaws. Test sample evaluation will return an array of values between 0 and 1 representing a similarity level with known samples. Results are scanned for the three largest values, and if any of them is similar enough to some known pathological tissue sample—the evaluated input will be marked as matching.

Tables 1 and 2 show results of the testing network with eleven normal tissue sample and 11 abnormal tissue samples in the learning set, evaluated against the training samples.

The network returned 0 false positives and 2 false negatives. This sums up to 10 % of the training set, and none of the errors was a falsely positive. Two samples wrongly classified as healthy tissue were probably too similar to healthy samples in the training set, and extending the learning set should correct that mistake (Fig. 4).

**Table 2** Abnormal tissue samples set test results

| | Best match | Second best | Third best | Conclusion |
|---|---|---|---|---|
| 1 | Healthy | Healthy | Healthy | Healthy |
| 2 | Healthy | Healthy | Sick | Healthy |
| 3 | Sick | Sick | Sick | Sick |
| 4 | Sick | Sick | Sick | Sick |
| 5 | Sick | Healthy | Sick | Sick |
| 6 | Sick | Sick | Healthy | Sick |
| 7 | Sick | Sick | Sick | Sick |
| 8 | Sick | Sick | Sick | Sick |

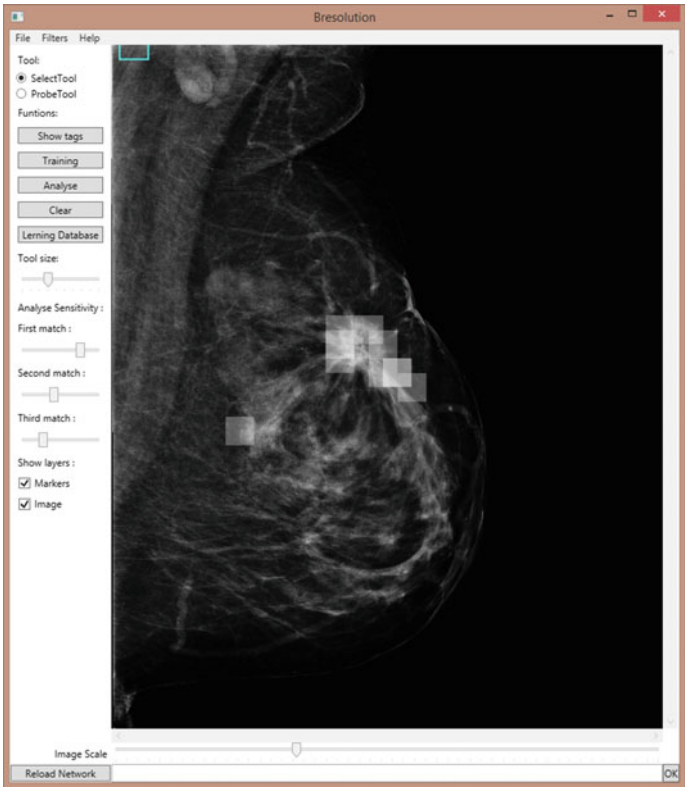


**Fig. 4** Main window of the system with evaluated image

## 5 System Interface

The system will be provided with a pre-learned network and corresponding database of samples. The main functionality of the system is to automatically evaluate the image and place semi-transparent white block in places where the tissue looks suspicious. Blocks are overlapping, so places with a greater density of markings will be much more visible. The algorithm places markers on the image if any of the first three best matches from the database is marked as abnormal, with specified threshold. Those threshold values were prepared in previous tests and calibrations, but can be tweaked online after the evaluation is done. For the following examples, sensitivities were not changed from the defaults. Three sample evaluations of images not used in the learning process are shown in Figs. 5, 6 and 7. In each, first image shows input, the second shows the returned markers and the third combines both images as they will be shown to the user. All samples show breasts categorized as category 5 of BI-RADS scale, and our markers are overlapping cancerous tissue parts.

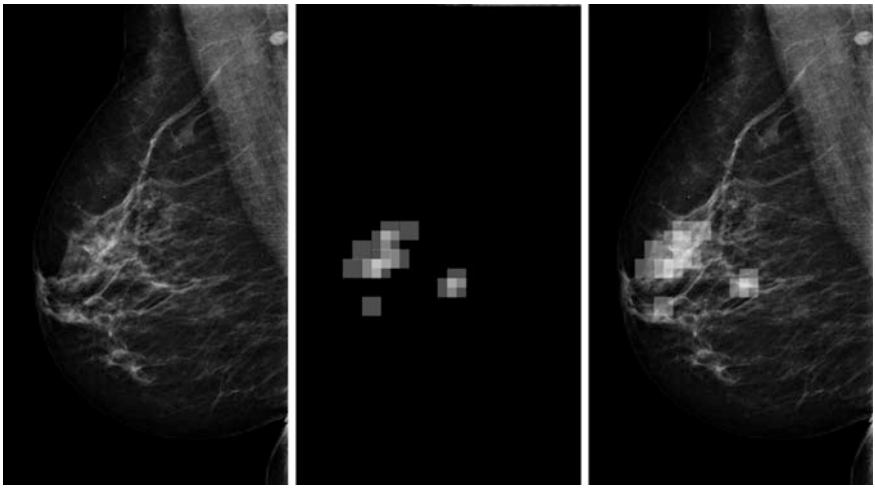

**Fig. 5** First evaluation example

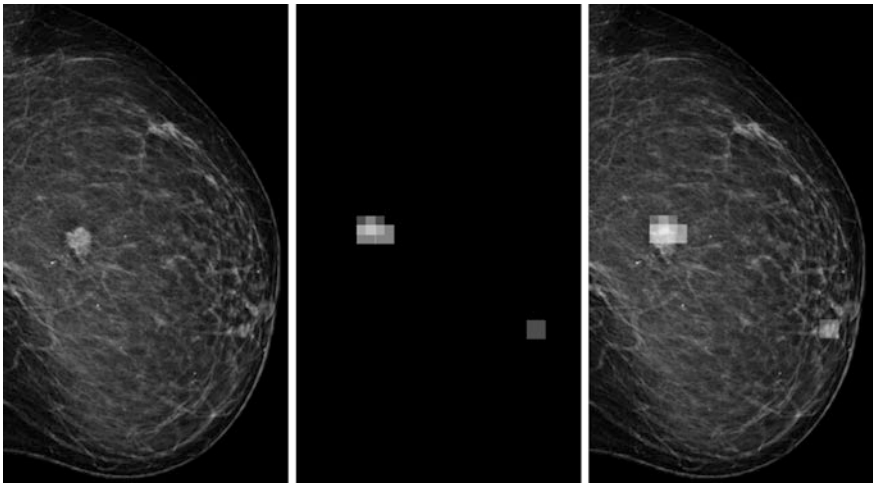

**Fig. 6** Second evaluation example

From this point, the user can use the probing tool to ask about any block on the image. All sub-block results will be compared, and the three best matching samples will be displayed as in Fig. 8.

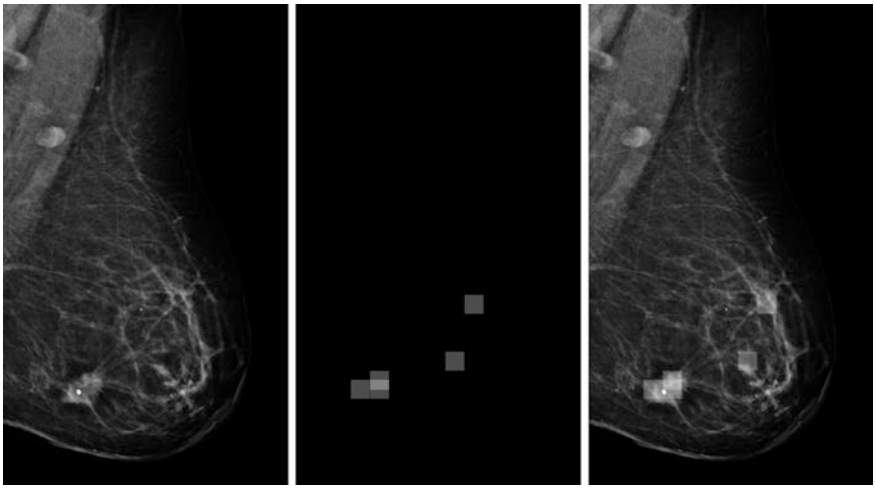

**Fig. 7** Third evaluation example

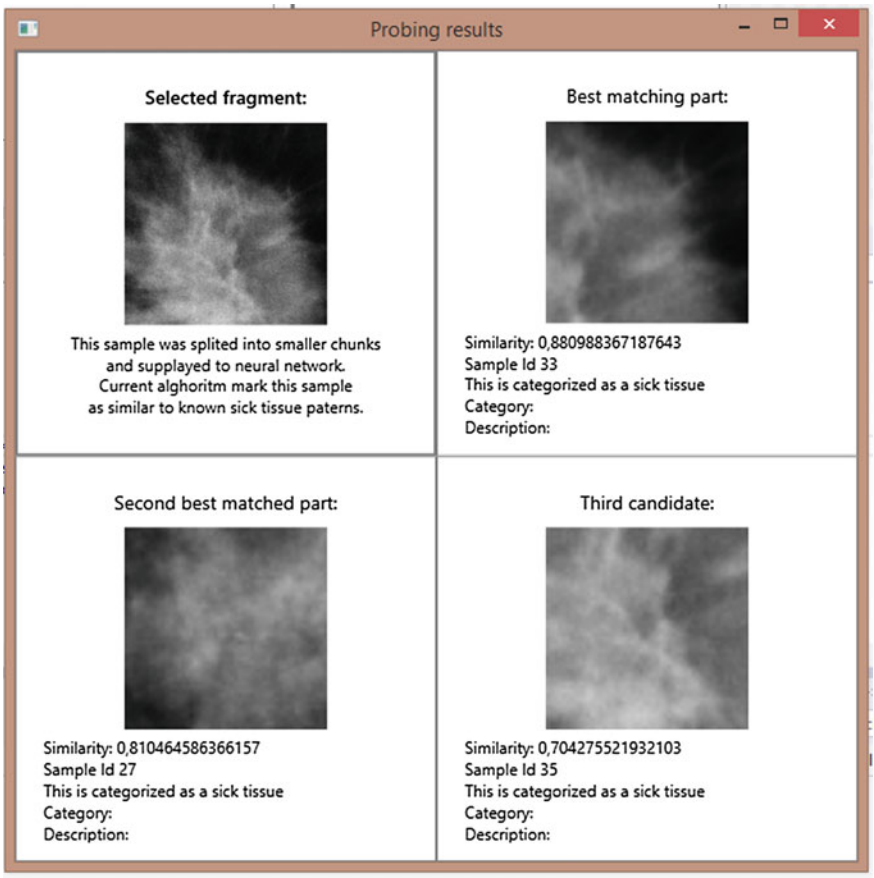


**Fig. 8** Specific image part close evaluation

## 6 Conclusions

The work described in this paper involved the design and implementation of an intelligent system for recognizing lesions in mammographic images. The artificial neural network incorporated a small modification to the standard backpropagation learning algorithm and turned out to be a good classifier of cancer changes. Previously used software has very high efficiency in the recognition of lesions but it also produced too many false positive results. The number of women exposed to breast cancer shows how big problem it is for today medicine. Program to prevent breast cancer start a few years ago in Poland. To increase the number of examined women radiologist are using mobile Mammography. The huge number of images created by radiologist in terrain requires quick and accurate describes—radiologist has only few minutes to find and describe cancer changes. Each images are described by at least two radiologist, but if there are some non-compliance than the third radiologist has to describe images and take a final decision. The huge number of images described every day and fatigue can lead to mistake.

That are the main reasons why working on alternative solutions of this problem is a valuable topic. The experimental results show that the modified networks perform well, and are a good predictor of future performance. Future research will concentrate on reducing the number of false positives while maintaining the good performance on true positives. If this is achieved, costs will be reduced, and patients will not be exposed to additional diagnostic tests.

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