

Performance analysis of a neuromodel for breast histopathology decision support system

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Article Info

Article history:

Received Jul 26, 2023

Revised Sep 1, 2024

Accepted Oct 8, 2024

Keywords:

Artificial neural networks

Breast cancer

Cancer

Decision support system

Histopathology

ABSTRACT

Breast cancer detection and diagnosis are crucial in reducing mortality rates among women globally. This research article explores an artificial intelligence technique for early breast cancer detection, aiding doctors in making informed decisions for improved patient management. The study employs histopathological analysis of breast tissue microscopically to detect abnormalities, with the aim of categorizing normal tissue, benign lesions, in situ carcinoma, and invasive carcinoma. The proposed technique utilizes an artificial neural network trained using the resilient backpropagation algorithm (RP_ANN). The study further compares the observed performance with those of three other algorithms, including gradient descent algorithm (GDA_ANN), Levenberg-Marquardt algorithm (LM_ANN), and layer sensitivity-based (LSB_ANN) algorithm based on various evaluation metrics. RP_ANN and LSB_ANN demonstrated superior performance, with high validation and training variance accounted for (VAF) and low root mean squared error (RMSE). The results underscore the potential of deep learning-based algorithms for improving breast cancer detection, promising better patient outcomes and enhanced diagnostic accuracy.

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1. INTRODUCTION

Breast histopathology is the study of breast tissue microscopically to detect and diagnose any abnormalities or diseases such as breast cancer. It is an essential part of breast cancer diagnosis and treatment planning. Breast cancer remains one of the major diseases leading to the death of women globally [1]–[4]. Breast cancer can be diagnosed through the initial palpation detection and regular checks using the ultrasound imaging examinations. The biopsy of the breast tissue is then performed after the diagnosis if the imaging examination shows a potential for malignant tissue growth. These biopsies of the breast tissues enable doctors to histologically evaluate the tissue's microscopic structure and components [5], [6]. In some cases, the number of such patients is significant which makes the diagnosis time consuming and complicated by the pathologist variability. It has therefore become important that computer aided assistance be made available for pathologists to make informed decision. This makes them concentrate on the cases that are most suspicious and to get around subjective interpretation in order to ensure the accuracy of the tested results. Breast cancer is categorized in a variety of ways for studies on prognosis and its genesis including by histology, stage, age at

diagnosis, and expression of tumor makers. Family history is another risk factor that needs to be considered. If one or two siblings, a parent, or both, have cancer, the risk of developing breast cancer doubles. The age at which the affected relative was diagnosed with the disease is also an important factor.

There is huge promise for the use of artificial intelligence (AI) in a clinical setting, from the automation of diagnostic procedures to therapeutic decision-making and clinical research. The information required is provided from numerous sources for diagnosis and therapy, including clinical notes, laboratory tests, pharmacy data, medical imaging, and genomic data. The microenvironment plays a crucial role in influencing various aspects of cancer, such as proteome mutations, cellular characteristics, genetic complexity, connections between tumor cells, cancer progression, and treatment effectiveness. To accurately assess these irregularities, it is essential to employ sensitive and precise techniques that can evaluate multiple features simultaneously. However, extracting numerous visual and morphometric features from pathological images is currently restricted by slide quality problems and tumor heterogeneity. Despite these limitations, utilizing AI-based analysis can help address the shortcomings of subjective visual and semi-quantitative evaluations by pathologists. This advanced approach allows for a comprehensive examination of complex tissue architectures, leading to a more thorough understanding of cancer pathology [7]–[16]. In other words, the use of AI techniques improves diagnostic accuracy even when imperfections in slide image quality would have made doing so extremely difficult. For instance, fuzzy logic can be used to mimic human judgement which makes the clinicians comprehend the classification process and findings easily. Other similar techniques include particle swarm optimization (PSO) algorithm, convolutional neural networks (CNNs), and other variants of deep learning algorithms. All these attempt to learn features directly from the raw data without the requirement for specialized input from pathologists [4], [7], [11], [13], [15].

Artificial neural networks (ANN) are interconnections of processing units known as neurons, which have been successfully used for data mining and prediction problems in a variety of applications [17]–[21]. Because ANN can simultaneously process information and make decisions, they can overcome otherwise complex problems [22]–[25]. The neural networks' ability to generalize from the input data to patterns already existing in the data makes them particularly suited for pattern recognition and classification problems. This paper develops an AI technique for the early breast cancer detection—a tool that has the potential of assisting physicians in making informed decisions about the best course of action for each patient, leading to more successful outcomes. With continued research and development, this neuromodel could play a critical role in the fight against breast cancer.

2. METHOD

The devastating effect of breast cancer - a prevalent form of cancer and the leading cause of cancer-related fatalities among women, can be reduced by timely and early detection. This detection is often done with the aid of analysis of histopathological images such as the one shown in Figure 1. Although the aforementioned technique has gained popularity for breast cancer detection, the technique still suffers from being time-consuming and labour-intensive. Additionally, the possibility of the existence of variations between different observers even under same conditions, has prompted the application of soft-computing and intelligence technique proposed in this work. The integration of well-trained intelligent decision support system in the management process possesses the potential of enhancing the quality of decision making as well as the speed thereof. The technique employed in this work includes the extraction of training data from breast cancer microscopy images of distinct groups including normal tissue, benign lesion, in situ carcinoma, and invasive carcinoma. Thereafter, the acquired data was used to train a carefully designed ANN using the resilient backpropagation algorithm.

2.1. The backpropagation algorithm and proposed enhancement

ANN are mainly interconnection of processing nodes called neuron, which have interconnecting weights that are modified according to a training rule. The performance of neural networks therefore depends, amidst other factors, on the chosen training algorithm or weight adaptation mechanism. The backpropagation algorithm is one of the most popularly utilized learning algorithms which has thus far been employed for numerous problems. The following are the steps utilized to train a feed forward ANN with the backpropagation algorithm:

Step 0: In this stage, all weights are set to zero or a small random value. Set weights to zero.

Step 1: This step iterates over steps 2 through 9 until a particular condition is met.

Step 2: This phase involves doing the calculations from steps 3 to 8 using the training patterns.

Step 3: The unit provides input to each input neuron in this step. ($X_i, i=1, \dots, n$).

Step 4: In this step each hidden unit ($Z_j, j=1, \dots, n$) receives weighted input from input layer and sums it, apply activation function, generates output of the hidden layer. The formula used to sum weight input signals is:

Performance analysis of a neuromodel for breast histopathology decision ... (Adedayo Olukayode Ojo)

$$Z_{in_j=v_{0j}} + \sum_{i=1}^n X_i V_{ij} \quad (1)$$

And the formula used to find output signals of hidden layer is $Z_j = f(z_{in_j})$ where f is the activation function.

Step 5: In this step each output unit sums its weighted input signals, and output signal is obtained by applying activation function on it.

$$y_{in_k} = W_{0k} + \sum_{j=1}^p Z_j W_{jk} \quad (2)$$

And the formula used to find output signals of hidden layer is:

$$y_k = f(y_{in_k}) \quad (3)$$

Step 6: In this step each output unit receives a target pattern corresponding to the input training pattern. The formula is:

$$\delta_k = (t_k - y_k) f'(y_{in_k}) \quad (4)$$

and then computes its error information terms. Its formula is:

$$\Delta W_{jK} = \alpha \delta_k Z_j \quad (5)$$

Step 7: the error at hidden layer is calculated by using the formula:

$$\delta_{in_j} = \sum_{k=1}^m \delta_k W_{jk} \quad (6)$$

calculates its weight correction term and velocity update using:

$$\delta_j = \delta_{in_j} f'(z_{in_j}) \quad (7)$$

$$\Delta v_{ij} = \alpha \delta_j X_i \quad (8)$$

Step 8: Update the weights from hidden layer to output layer and weights from input layer to hidden layer. The formula is as:

$$w_{if(new)} = w_{jk(old)} + \Delta W_{jk} \quad (9)$$

$$v_{if(new)} = v_{if(old)} + \Delta v_{jk} \quad (10)$$

Step 9: in this step the stopping condition is tested.

In this study, the backpropagation neural network (BPNN) algorithm introduces five variable learning rate strategies. These strategies involve selecting different learning rate values from a predefined range. The learning rate schemes include mechanisms for growing, decreasing, chaotic, and oscillating rates of learning. To explore the behavior of the BPNN algorithm when combining multiple natural learning rates, this work proposes a hybrid learning rate scheme. This scheme comprises a randomized pool of five additional learning rates, each exhibiting distinct behaviors. Overall, this work presents learning mechanisms that allow for variable changes in the learning rate.

2.2. Description of artificial neural networks

This section describes the feature, architecture and procedures taken in the design of the ANN. The neural network was developed, trained and tested in the MATLAB software computing environment. The training dataset, already separated into input and target data, was loaded. These data were split into training of 70% (399 samples in the dataset), validation 15% (85 samples in the dataset) and testing sets 15% (85 samples in the dataset). Feedforward net function was used to create network with a single hidden layer of 10 neurons. The training algorithm (resilient backpropagation) was thereafter specified. Other training parameters were then set for the network, including the number of epochs, the training goal, the minimum

gradient, and the maximum number of validation failures. After training the network, it was tested on the dataset and the observed result was visualized.

Figure 2 shows the neural network architecture which has five inputs and three outputs using the datasets for the breast cancer detection. The inputs include radius mean, texture mean, perimeter mean, area mean, and smoothness while the output include concave point, symmetry and fractual dimension. 10 neurons were used for the hidden layer for training and testing of the data. The backpropagation algorithm was employed in updating the weight elements of the neural network architecture based on the observed error. The back propagation algorithm helps to improve the training process by employing a learning rate dynamically. The performance of the breast cancer detection model trained using this algorithm would depend on various factors, including the quality and size of the dataset, network architecture, hyperparameter settings, and the choice of the variable learning rate method.

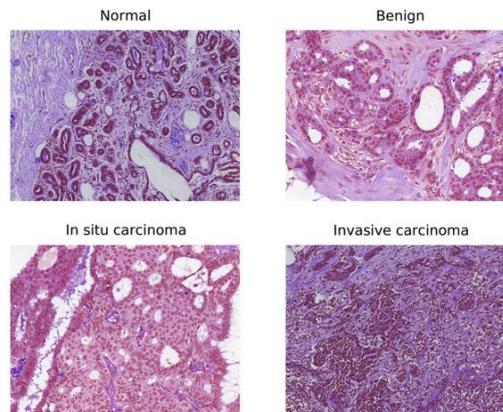


Figure 1. Typical images showing normal, benign, insitu carcinoma, and invasive carcinoma [4]

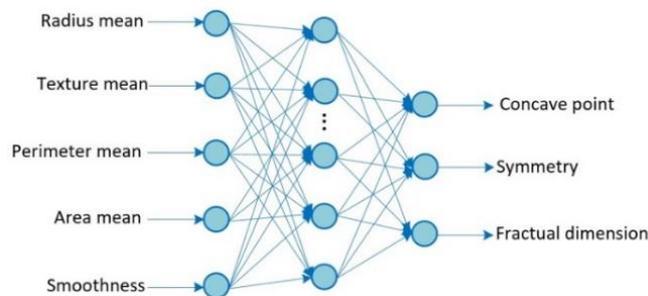


Figure 2. The architecture of the neural network

3. RESULTS AND DISCUSSION

After the training and testing of the ANN. The regression plot provided valuable insights into the relationship between the neural network output and the expected values as evidenced in Figure 3. We observed a significant positive slope, indicating that certain network features have a direct impact on the detection of intrusions. This suggests that as these features increase, the likelihood of accurately detecting breast cancer also increases. Additionally, the intercept value provided an estimate of the detection likelihood when all network features are zero.

Figure 4 represents the 3D visualization of selected section of data set used in predicting breast cancer detection. This particular section includes the surface texture, the radius of the lobes, and the area of the lobes. Where the lobes refer to the section of the breast that contains the glandular tissues. From the plot, it can be observed that the area is uniform for a range of radius and surface texture, and then increases rapidly when the radius of the lobes increases above a certain size. By visualizing this plot, the patterns of possible breast cancer features can easily be identified.

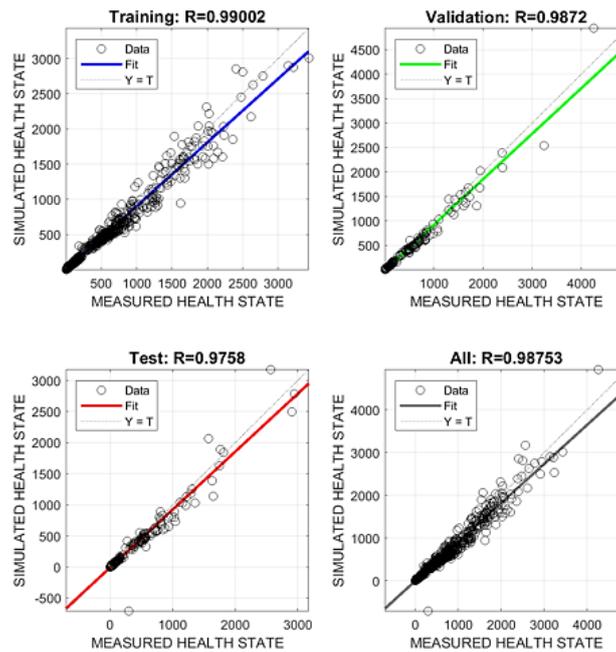


Figure 3. The regression plot for breast cancer detection

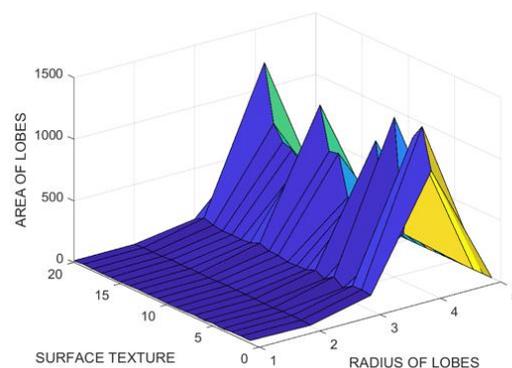


Figure 4. Overview of selected variables

This work compares different algorithms for training the neural network for breast cancer detection mainly artificial neural network trained using the resilient backpropagation algorithm (RP_ANN), layer sensitivity-based artificial neural network (LSB_ANN), Levenberg-Marquardt artificial neural network (LM_ANN), and gradient descent algorithm (GDA_ANN). RP_ANN exhibits exceptional accuracy, with 98.64% training variance accounted for (VAF) and 97.77% validation VAF as shown in Table 1. It demonstrates proficiency in learning complex patterns and generalizing to unseen data, making it a promising candidate for clinical implementation. LSB_ANN also performs well, with 97.82% training VAF and 97.65% validation VAF, showing its potential as an effective breast cancer detection tool. LM_ANN shows promise with 97.51% training VAF and 96.08% validation VAF, but its relatively higher root mean squared error (RMSE) suggests room for improvement in predictive accuracy. GDA_ANN performs lowest, with 96.33% training VAF and 96.24% validation VAF, indicating limitations in predictive accuracy compared to the other algorithms. Overall, deep learning-based algorithms like RP_ANN and LSB_ANN hold potential for improving breast cancer diagnosis. Their high VAF values and strong correlations demonstrate their efficacy in accurately classifying breast cancer subtypes from microscopy images. Implementation of these algorithms could lead to timely interventions and reduced disease burden on patients and healthcare systems. However, the study acknowledges certain limitations, including the need for a larger dataset and real-world clinical validation to assess the algorithms' effectiveness. Future research and development in automated breast cancer detection hold promise for transformative impacts on global healthcare.

Table 1. Performance comparisons of several algorithm for breast cancer detection

Network	Training		CMD	Testing	
	Training VAF	Validation VAF		VAF	RMSE
RP_ANN	98.64	97.77	0.9841	96.26	4.38
GDA_ANN	96.33	96.24	0.9666	94.09	7.98
LM_ANN	97.51	96.08	0.9874	93.57	4.14
LSB_ANN	97.82	97.65	0.9877	97.81	3.97

4. CONCLUSION

In this study, an ANN based neuromodel serving as a breast histopathology decision support system was developed. The analysis of the performance of the neuromodel shows that it has the ability to provide valuable support in analysing breast histopathology samples. The network was trained with the resilient backpropagation algorithm using data extracted from clinical source. Furthermore, the performance of the trained network, in comparison with other networks with similar parameters, indicated that the proposed neuromodel is a valuable tool in the management process of breast cancer. This work, therefore, showcases the accuracy and applicability of neuromodels in medical diagnosis. The model, which is capable of identifying the various patterns of histopathology and making reliable predictions, represents a critical development in breast cancer diagnosis and treatment programs.

ACKNOWLEDGEMENTS

This paper is financed by the DAAD NiReMaS Project of the University of Cologne, Germany.

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Performance analysis of a neuromodel for breast histopathology decision ... (Adedayo Olukayode Ojo)

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