ORIGINAL ARTICLE

Comparative Analysis of Artificial Neural Networks and Extreme Learning Machine Techniques for Breast Cancer Diagnosis

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Abstract

Background: Breast cancer is the second dangerous disease that causes death in women. Early detection can reduce mortality rates by 40% or more. The procedures to be carried out in this process create extra labor and financial costs for both the patient and the hospital.

Objective: This study aims to use artificial neural networks and extreme learning machine techniques in the correct diagnosis of breast cancer and to evaluate the applicability of the results in health services and management.

Methods: In our study; a dataset containing numerical information about different breast mass, which indicates which mass is benign and which mass is malignant cancer, has been used. The dataset comprises diagnostic information of 569 patients and includes 6 variable parameters.

Results: In the study, the mass found in individuals given in the dataset is trained with deep learning models obtained with artificial neural networks and extreme learning machines and was determined if it is benign or malignant. In the test dataset, the best estimation result is found to be a 92% accurate prediction with the extreme learning machine. The highest accurate estimation rate achieved with artificial neural networks is 90%.

Conclusion: In the study, the technique of extreme learning machine gave better results in terms of both accuracy and learning time. Also, it shows that the extreme learning machine method can be adapted to healthcare processes and used rapidly on patient data during diagnosis and later stages.

Keywords: *Breast cancer, artificial neural networks, extreme-learning machine, cancer detection.*

INTRODUCTION

Breast cancer is the second dangerous disease that causes death in women [1]. Early detection can reduce mortality rates by 40% or more. Mammography was used to detect the disease before, but it is not preferred in developed countries as it poses a health risk to patients. While the use of ultrasound is preferred today, the evaluation of the results is based on the experience and expertise of the doctor [1]. It is predicted that 7% of Western women will develop a cyst in their breasts during their life [2]. Although many of these cysts can turn into cancer, most are usually benign. It is difficult to determine whether they are benign or malignant in mammography examinations. Therefore, the patient can be called for a second diagnosis and a needle biopsy can be performed [3]. The procedures to be carried out in this process create extra labor and financial costs for both the patient and the hospital. An increase in such cases in health services prevents the quality management of health services. The correct determination of the results in these processes is a life-saving factor, while delays and errors in the process affect the treatment negatively.

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Computer-aided diagnosis and diagnostic methods are getting more and more popular day by day. One of the application areas of these methods is the detection and diagnosis of breast masses. In the traditional method, the relevant mass is detected and then it is determined to be either benign or malignant [4].

Deep learning methods are most preferred among artificial intelligence methods in health services and management processes [5]. The fact that deep learning methods are more complex and the ability to process images and complex data models causes this to be preferred in this field [6]. In some studies on deep learning, the algorithm has been found to achieve better sensitivity than pathologists [7]. Delay in such diagnoses poses a serious risk in rural areas or regions where specialist physicians are scarce. With expert systems developed using artificial intelligence methods, it can support diagnosis and diagnosis processes in regions where there is no specialist.

One study used convolutional neural networks to determine whether lymph nodes in the chest were pathologically benign or malignant [8]. Another study evaluated the risk of malignancy in a mass of the breast using ultrasound images and deep learning architectures, with the highest accuracy rate of 87.5% when compared with mammography and pathological procedures [9].

Table 1: Feature correlation matrix.

Feature	Mean Radius	Mean Texture	Mean Perimeter	Mean Area	Mean Smoothness	Diagnosis
mean_radius	1.00	0.32	1.00	0.99	0.17	-0.73
mean_texture	0.32	1.00	0.33	0.32	-0.023	-0.42
mean_perimeter	1.00	0.33	1.00	0.99	0.21	-0.74
mean_area	0.99	0.32	0.99	1.00	0.18	-0.71
mean_smoothness	0.17	-0.023	0.21	0.18	1.00	-0.36
Diagnosis	-0.73	-0.42	-0.74	-0.71	-0.36	1.00

Deep learning methods are gaining popularity day by day in health services and management processes. Artificial neural networks and extreme learning machines are two subtypes of deep learning [10]. Artificial Neural Networks are structures made up of intertwined neurons similar to the human brain. Neurons are connected by weights. Weight values are updated in the learning process and accordingly, which neurons are triggered. It has a model similar to the work of the autonomic nervous system [11]. Extreme learning is a three-step algorithm without feedback-based learning iterations like artificial neural networks. In the dataset, each parameter is assigned random weights. Accordingly, the weights of the hidden layers are determined by applying this layer to the Moore-Penrose inverse process [12]. Therefore, it can be trained very quickly. It is used in areas such as diabetes disease detection and protein classification in health services and management [13]. This study applied and compared artificial neural networks and extreme learning machines in the diagnosis of breast mass, with a dataset created by the University of Wisconsin, containing numerical information on benign and malignant breast mass. By adhering to supervised training methods, the success and execution time for artificial neural networks and extreme learning machines were evaluated.

MATERIALS AND METHODS

Our study used a dataset created by the University of Wisconsin, containing numerical information about different breast masses, and their benignity or malignancy. The dataset contains diagnostic information of 569 patients, consisting of 6 different columns. 80% of the patients were used for training and 20% as test data. The features used in the dataset were:

Mean Radius: Mean distance from the center to points on the perimeter.

Mean Texture: Standard deviation of gray-scale values.

Mean Perimeter: Total perimeter length of the tumor.

Mean Area: Total area of the tumor.

Mean Smoothness: Variation in the local radius lengths.

Diagnosis: Malignant (M): (indicating cancerous tumors), Benign.

There are 357 (63%) benign and 212 (37%) malignant patients in the dataset. The parameters used in the dataset are the average values of the masses detected in the images obtained by mammography. The data was obtained by the University of Wisconsin and patient consents were taken during the data collection period [14]. Since the dataset is publicly available no ethical approval was obtained.

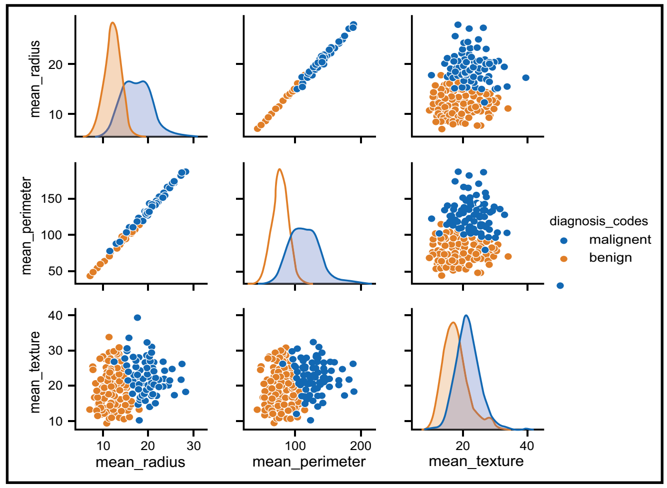

Fig. (1): Pair plot of data features based on diagnosis.

In the preliminary examination, the correlation relationship between the diagnosis column and other columns was examined. Mean_radius, mean_perimeter, mean_area columns show the highest negative correlation with diagnosis. In the dataset we studied, this finding shows that these three columns are more important in cancer detection. Correlation relations of the columns in the dataset are shown in Table **1**.

In the dataset, the distribution of benign or malignant cancerous masses depending on the relationship between the columns is shown in **Fig. (1)**. When the mean_texture column is correlated with mean_radius and mean_perimeter, the benignity of the mass can be classified.

In this dataset, artificial neural networks and extreme-learning machine methods were trained with similar parameters, and each method was repeated 10 times to compare average accuracy and training times. Algorithms were executed in a Python programming language with the keras library. Both models were trained and tested with different numbers of hidden neurons as hyperparameters. In tests performed with artificial neural networks, one input layer and a hidden layer with 10, 50, 90, and 130 hidden neurons were trained and the test results were evaluated. In training, 100 epoch, 50 as batch_size were used with a learning rate of 0.001, and Adam (A Method for Stochastic Optimization) optimization was used. In tests performed with an extreme learning machine, 10, 50, 90, and 130 hidden neurons were trained and the test results were evaluated. The weights of the input values were assigned randomly, and the weights of hidden neurons were obtained by taking the weights obtained from the input values by the inverse of the Moore Penrose of the matrix. Backpropagation was not used for training. The results were evaluated with accuracy and execution time metrics in the test dataset.

STATISTICAL ANALYSIS

Both extreme-learning machine and artificial neural network models were tested 10 times and the results were compared by using a t-test in Minitab statistical software. The results demonstrated a value of 0.015 ($p<0.05$) which showed that results obtained from both models are statistically different.

RESULTS

A dataset with characteristics of 569 patients diagnosed with breast mass, with each case labeled as either malignant (cancerous) or benign was used. In the test dataset, the best estimation result was found as

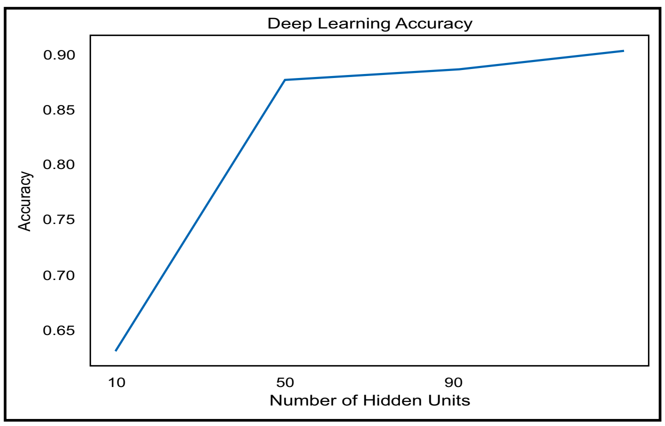

Fig. (2): Neural network test accuracy.

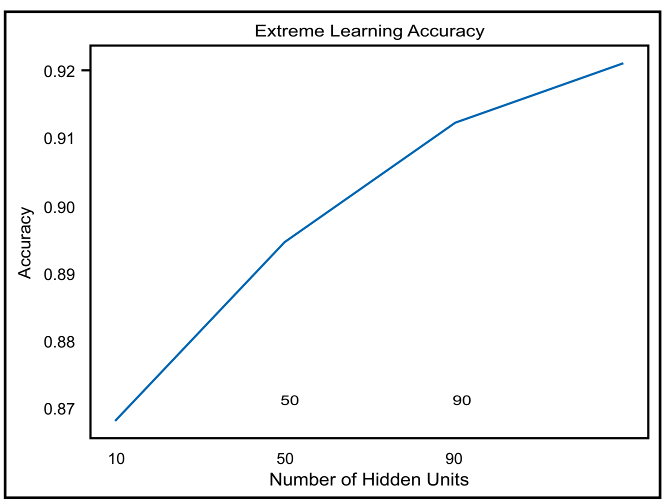

Fig. (3): Extreme Learning *vs.* Hidden Nodes

Table 2: Artificial neural network accuracy and execution time.

Artificial Neural Network Accuracy				
Hidden Units Count	10	50	90	130
Average Test Accuracy	63%	87%	88%	90%
Average Training Execution time [ms]	5400	6100	5980	5840

Table 3: Extreme learning accuracy and execution time.

Extreme Learning Accuracy				
Hidden Units Count	10	50	90	130
Average Test Accuracy	86%	89%	91%	92%
Average Training Execution time [ms]	0,96	0,997	0,998	1,9

92% with the extreme-learning machine. The highest accurate estimation rate achieved with artificial neural networks was 90%. Regarding the execution times for training, the most complex extreme learning machine model completed its training in 1.9 ms. The training of a similar complex model created with artificial neural networks took 5840 ms.

In tests performed with artificial neural networks, we used an artificial neural network with an input layer with a hidden layer consisting of 10, 50, 90, and 130 hidden neurons respectively, and an output layer with a single neuron layer for binary classification. Parameter optimization was done on the number of neurons in the hidden layer. In training, 100 epoch, 50 as batch_size with a learning rate of 0.001 were used. Adam (A Method for Stochastic Optimization) optimization was used. Accuracy rates depending on the number of hidden neurons used in the test set are shown in **Fig. (2)**. The accuracy rate was stable at around 90% with 50 hidden neurons and with more hidden neurons there is not a significant change in accuracy.

In tests performed with an extreme learning machine, 10, 50, 90, and 130 hidden neurons were trained and the test results were evaluated. The best test result was obtained using 130 hidden neurons with 92% accuracy. Unlike artificial neural networks, as the number of hidden neurons increased, the accuracy also increased (**Fig. 3**).

In the study, the execution time for training the artificial neural networks and the extreme-learning machine was examined in parallel with the accuracy rates in the test data. The average execution time for training and accuracy rates for 10 training and tests with different numbers of hidden neurons are given in Table **2**. With artificial neural networks, the best accuracy average is 90% and the time spent in training is 5840 ms. Increasing the number of samples in the dataset, increasing the number of epoch used, batch size, and the number of hidden neurons are the parameters that affect this period in direct proportion.

The highest test accuracy was 92% and the training time was 1.9 ms in the tests performed with an extreme learning machine. The number of hidden neurons used has increased training time but has become much faster than artificial neural networks (**Table 3**). In Decision points requiring rapid integration in healthcare and management processes, rapid adaptation time, and test accuracy for diagnosis and other support systems, extreme learning can be used in such kinds of problems.

DISCUSSION

Rapid developments in technology and the increasing use of artificial intelligence in health have put the health sector in a process of change [14]. Reasons such as the increase in the elderly population, the increase of chronic diseases, and difficulties in delivering health services to rural areas in developed countries encourage the use of artificial intelligence-supported machine learning techniques for improvement in health care processes [15].

In a study, artificial intelligence methods used in the field of health were examined. 85% of supervised machine learning was used in machine learning-based studies such as estimation and classification. The most preferred algorithm was the Support Vector Machine (SVM). Machine learning is most commonly used in the estimation, diagnosis, and determination of post-disease complications, thereby saving patients' time and workloads to provide better healthcare services to patients [16].

In the results obtained from our study, the success of deep learning methods in the diagnosis of breast cancer has been revealed. Since deep learning models may require high hardware and time during the training and formation stages, it has been shown that simpler models such as an extreme learning machine will save time and cost. The highest accurate estimation rate achieved with artificial neural networks is 90%. Learning with 130 hidden neurons lasted 5840 ms. In a similar study, breast cancer risk was calculated using artificial neural networks, and its accuracy rates were seen between 82-90% [17]. Regarding the extreme learning machine, the success rate increased to 92% with the same number of neurons. When it comes to the training time, the extreme learning machine model, which has 130 hidden neurons, completed its learning in 1.9 ms. In terms of duration, it completed its education in approximately 3000 times less time. In another study, it was determined that the masses in the chest were good or malignant by using an extreme learning machine. Success is seen as 98.9% in a more complex model and wider dataset [18].

In another study, researchers compared six machine learning algorithms—GRU-SVM, Linear Regression, Multilayer Perceptron (MLP), Nearest Neighbor search, Softmax Regression, and Support Vector Machine (SVM)—to classify breast cancer tumors as malignant or benign. The dataset was split into 70% for training and 30% for testing. Among the algorithms, the Multilayer Perceptron achieved the highest test accuracy of approximately 99.04%, indicating its effectiveness in breast cancer classification tasks [19].

Another study introduced a two-layer neural network model called the Higher-Order Probabilistic Perceptron (HOPP), designed to implement Bayesian inference by systematically including correlations among input variables. The model was applied to the Breast Cancer Wisconsin (Diagnostic) Dataset to classify tumors as malignant or benign, assigning probabilities to each outcome. Trained on 90% of the dataset and tested on the remaining 10%, the HOPP model achieved classification accuracies of up to 97%, with a standard deviation of around 2% [20]. The extreme learning machine method can be adapted to healthcare processes and used rapidly on patient data during diagnosis [21].

CONCLUSION

In this study, the technique of extreme learning machine gave better results in terms of both accuracy and learning time also, it shows that the extreme learning machine method can be adapted to health care processes and used rapidly on patient data during diagnosis and later stages.

ETHICS APPROVAL

Since the dataset used for this study is publicly available, no ethical approval was obtained.

CONSENT FOR PUBLICATION

Not applicable.

AVAILABILITY OF DATA

This study used a dataset created by the University of Wisconsin.

FUNDING

None.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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Declared none.

AUTHORS' CONTRIBUTION

All authors contributed to the design and drafting of the manuscript. Ozan Veranyurt contributed to the statistical analysis and acquisition of data. All authors participated in interpreting data, critical revision, and final approval of the submitted manuscript.

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