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ARAŞTIMA MAKALES/ RESEARCH ARTICLE

Application with Multilayer Perceptron and Radial Basis Function from Neural Network-Based Methods to Predict Cervical Cancer

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Abstract

Objective: Cervical cancer is the fourth most prevalent malignancy among women worldwide. Low- and middle-income countries are much more burdened than high-income nations. Therefore, the need to develop new diagnostic techniques to predict the course of the disease and the prognosis of this malignancy has increased. In this study, cervical cancer will be classified to create an accurate diagnostic predictive model using the machine learning method The Multilayer Perceptron (MLPNN) and Radial Based ANN (RBFNN), and disease-related risk factors will be determined.

Methods: This current study considered the open-access data set of patients that cervical cancer and no-cervical cancer samples. For this purpose, data from 72 patients were included. The data set was divided as 80:20 as a training and test dataset. MLPNN and RBFNN were used for the classification Accuracy, specificity, AUC, positive predictive value, and negative predictive value performance metrics were evaluated for model performance.

Results: Among the performance criteria in the test stage obtained from the RBFNN model that has the best classification result; accuracy, specificity, AUC, positive predictive value, and negative predictive value were obtained as 92.3%, 100.0%, 96.5%, 100.0%, and 91.6%, respectively. According to the variable importance obtained as a result of the model, the variables most associated with the diagnosis were behavior sexual risk, empowerment abilities, and motivation strength, respectively.

Conclusion: The applied machine learning model successfully classified cervical cancer and created a highly accurate diagnostic prediction model. With the parameters determined as a result of the modeling, the clinician will be able to simplify and facilitate the decision-making process for the diagnosis of cervical cancer.

Key Words: Cervical cancer, classification, machine learning, Multilayer Perceptron, Radial Based ANN.

Sinir Ağı Tabanlı Yöntemlerden Çok Katmanlı Algılayıcı ve Radyal Bazlı Sinir Ağı ile Rahim Ağzı Kanserini Tahmin Etmek için Uygulam

Özet

Amaç: Rahim ağzı kanseri dünya çapında kadınlar arasında en sık görülen dördüncü malignitedir. Düşük ve orta gelirli ülkeler, yüksek gelirli ülkelerden çok daha fazla yük altındadır. Bu nedenle, hastalığın seyrini ve bu malignitenin prognozunu tahmin etmek için yeni teşhis tekniklerinin geliştirilmesi ihtiyacı artmıştır. Bu çalışmada Çok Katmanlı Algılayıcı (MLPNN) ve Radyal Tabanlı Yapay Sinir Ağları (RBFNN) makine öğrenimi yöntemleri kullanılarak rahim ağzı kanserini sınıflandıran bir tahmin modeli oluşturmak ve hastalıkla ilişkili risk faktörleri belirlemektir.

Metod: Bu çalışmada, rahim ağzı kanseri olan ve rahim ağzı kanseri olmayan hastaları içeren açık erişim veri seti dikkate alınmıştır. Bu veri setinde toplam 72 hasta bulunmaktadır. Veri seti eğitim ve test veri seti olarak 80:20 olarak bölünmüştür. Sınıflandırma için MLPNN ve RBFNN kullanılmıştır. Modelin performansı doğruluk, seçicilik, AUC, pozitif tahmin değeri ve negatif tahmin değeri performans metrikleri ile değerlendirildi.

Bulgular: En iyi sınıflandırma sonucuna sahip olan RBFNN modelinden elde edilen test aşamasındaki performans kriterlerinden; doğruluk, seçicilik, AUC, pozitif tahmin değeri ve negatif tahmin değeri sırasıyla %92.3, %100.0, %96.5, %100.0 ve %91.6 olarak elde edilmiştir. Model sonucunda elde edilen değişken önemliliklerine göre tanı ile en çok ilişkili değişkenler sırasıyla riskli cinsel davranış, güçlendirme yetenekleri ve motivasyon gücüdür.

Sonuç: Uygulanan makine öğrenimi modeli, rahim ağzı kanserini başarılı bir şekilde sınıflandırmıştır ve yüksek doğrulukta bir tanısal tahmin modeli oluşturulmuştur. Modelleme sonucunda belirlenen değişkenler ile klinisyenlerin rahim ağzı kanseri tanısına karar verme süreci basitleştirebilecek ve kolaylaştırabilecektir.

Anahtar Kelimeler: Rahim ağzı kanseri, sınıflandırma, makine öğrenimi, Çok Katmanlı Algılayıcı, Radyal Tabanlı Yapay Sinir Ağları.

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INTRODUCTION

Cervical cancer is one of the most common cancers in women. It is the third rank in the world, and it is reported that approximately 569 thousand women are diagnosed with cervical cancer every year and 311,000 women die due to cervical cancer (1). Human papilloma virus (HPV) is considered to be the primary cause of cervical cancer worldwide. Cervical cancer is one of the preventable types of cancer, and comprehensive planning based on vaccination against HPV and regular HPV-based screening has been shown to be cost-effective in almost all countries. However, due to the difficulty of accessing the vaccine in underdeveloped countries and the inadequacy of cervical cancer screening, the measures are not to the desired extent (2).

The way to reduce the number of deaths from cervical cancer is early detection. Especially in countries where screening programs are not available, early detection of this type of cancer and initiation of effective treatment significantly increases the probability of survival. Under current circumstances, this disease is often not diagnosed until it has progressed, or treatment is available. This causes a high mortality rate in cervical cancer. By understanding and detecting the symptoms of cervical cancer, patients can be diagnosed early (3).

Researchers working in the field of machine learning (ML) are always seeking to produce improved prediction models that are able to understand the most recent data in the sector of cervical cancer. It has been shown that predictive models that are developed via the use of machine learning techniques may be of assistance in the process of cervical cancer detection (4). The Artificial Neural Network (ANN) is one of the machine learning techniques that is used the most (5).

ANN, one of the artificial intelligence methods, is a computational tool based on the properties of biological nervous systems. ANN is a data processing technique developed to solve very complex problems with the help of computers, consisting of a large number of processing elements connected to each other through weighted links, each of which has its own memory (6). It is a method of processing data on a computer that imitates the way biological neurons carry out their functions and evaluates the connection that exists between a system's inputs and its outputs. The neuron, also known as a node, is the main component of an ANN and the primary building block of the information processing system (7). This machine learning approach has several levels, including inputs, outputs, and hidden layers. The input layer is a layer that doesn't do any computing but gets information from the outside world. The number of input and output variables is equal to the number of nodes in the input and output layers. ANN have been shown to be useful for a number of tasks, such as predicting, modeling, and classifying (8).

The Multilayer Perceptron ANN (MLPNN) is an ANN model for dealing with problems that don't follow a straight line. It is a feed-forward backpropagation network with at least one layer and at least three levels between the input and output layers (9). During the forward propagation stage, while the network's performance and error value are being computed, the relation weight values across the layers are modified to reduce the error value seen during reverse propagation (10).

Radial Based ANN (RBFNN) networks are composed of three layers: an input layer, an output layer, and a hidden layer. It is an ANN model based on neuron cells in the human nervous system. The RBFNN example's training performance becomes an interpolation issue by locating the closest result to the data in the output vector space. RBFNN structures, like ANN structures, normally comprise of an input layer, a hidden layer, and an output layer. However, unlike other ANNs, when the data is sent from the input layer to the hidden layer, it is subjected to radial-based activation functions and a non-linear cluster analysis. The structure between the hidden layer and the output layer functions similarly to other ANN types, and the real training occurs in this layer (11).

The goal of this work was to classify cervical cancer using the open-access "Cervical Cancer Behavior Risk Data Set," to compare the predictions of MLPNN and RBFNN, and to find the risk factors for cervical cancer using these techniques.

METHODS

Dataset

The open access “Cervical Cancer Behavior Risk Data Set” data set to be used in the study can be accessed at https://archive.ics.uci.edu/ml/datasets/Cervical+Cancer+Behavior+Risk#. There are 72 patients in the data set used. Twenty-one of these patients were cervical cancer and 51 of them were non-cervical cancer patients.

Artificial Neural Network Models

Because of their efficiency, adaptability, and usability, artificial neural networks are the chosen solution for many predictive data mining applications. Predictive neural networks are very beneficial in applications with complicated mechanismsIn the past few years, people have become more interested in using neural networks to solve problems that can't be solved with traditional methods. ANN has been used successfully in many medical applications. Unlike traditional spectrum analysis methods, artificial neural networks not only model signals but also create signal categorization solutions. Another benefit of artificial neural networks over traditional approaches for interpreting biological data is their speed once trained. As seen in Figure 1 shows that each layer is made up of a number of nodes.

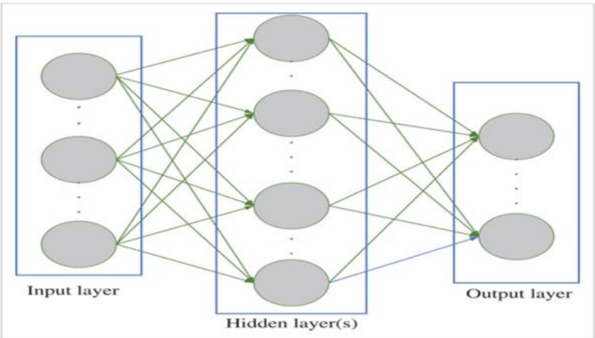

Figure 1. ANN model's structure

MLPNN is a model that that shows how an input vector maps to an output vector in a way that is not linear. It consists of a network of fundamental, interconnected neurons or nodes. Nodes are connected by weights and output signals, and the sum of each node's inputs is replaced by a simple nonlinear transfer or activation function (12).

RBFNN was created in 1908, and it became part of the history of ANN when it was used to solve the problem of filtering. The impact response characteristics seen in biological nerve cells inspired it. RBFNN model training may be conceived of as a multi-dimensional curve-fitting technique. RBFNN models, like normal ANN architecture, are separated into three layers: input, secret layer, and output layer. Unlike traditional ANN architectures, The progression from the input layer to the hidden layer in RBFNNs is accomplished through the application of radial-based activation functions and nonlinear cluster analysis. The structure of the hidden layer and output layer is the same as in previous ANN types (13).

Statistical analysis

In order to establish whether or not the data followed a normal distribution, the Shapiro-Wilk test was carried out. Quantitative data that did not fit the normal distribution were presented as the median (minimum-maximum). The Mann-Whitney U test was performed to determine whether there was a statistically significant difference in terms of independent variables between the cervical cancer (Target variable) categories "no cervical cancer" and "have cervical cancer". $p<0.05$ was considered statistically significant. IBM SPSS Statistics 26.0 package application was used for all analyzes.

RESULTS

Table 1 contains descriptive information for the independent variables investigated in this research. In terms of, behavior sexual risk, intention commitment, behavior personal hygine, intention aggregationperception vulnerability, norm fulfillment, perception severity, motivation willingness, , norm significant person, social support appreciation, social support emotionality, empowerment abilities, empowerment knowledge, motivation strength, empowerment desires variables, there is a statistically significant difference (p<0.05).

Table 2 shows the values of the performance metrics obtained from the models built to predict cervical cancer in the test stage.

The accuracy, specificity, AUC, positive predictive value and negative predictive values obtained from the MLP method for the modeling test data set are 88.9%, 100.0%, 100.0%, 100.0%, and 81.8% respectively.

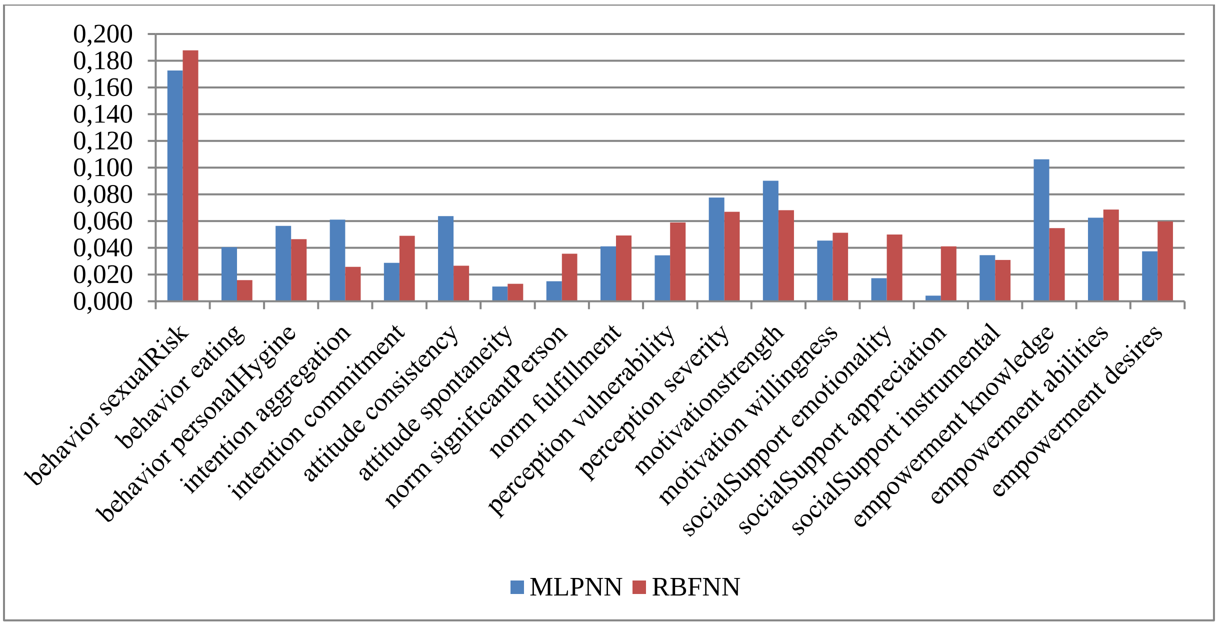

Figure 2. The importance values for possible risk factors

The accuracy, specificity, AUC, positive predictive value and negative predictive value values obtained from the RBF method are 92.3%, 100.0%, 96.5%, 100%, and 91.6% respectively.

In this research, the importance values of the factors associated with cervical cancer are shown in Table 3 while the values for these percentages of importance are represented in Figure 2.

Table 2. In the testing stage, performance metric values are calculated from constructed models.

Model / Performance Metrics	MLPNN Value	RBFNN Value
Accuracy (%)	88.9	92.3
Specificity (%)	100.0	100.0
AUC	1	0.965
Positive predictive value (%)	100.0	100.0
Negative predictive value (%)	81.8	91.6

AUC: Area under the ROC curve

Table 1. Descriptive statistics for quantitative independent variables

Variables	Ca cervix		p value*
	No cervical cancer	Has cervical cancer	
	Median	Median	
Behavior Sexualrisk	10 (6-10)	10 (2-10)	**0.003**
Behavior Eating	13 (3-15)	15 (11-15)	0.106
Behavior Personalhygine	11 (5-15)	9 (3-15)	**0.004**
Intention Aggregation	10 (2-10)	6 (2-10)	**0.004**
Intention Commitment	15(7-15)	14 (6-15)	**0.019**
Attitude Consistency	7 (2-10)	8 (5-10)	0.220
Attitude Spontaneity	8 (4-10)	9 (6-10)	0.673
Norm Significantperson	5 (1-5)	1 (1-5)	**0.014**
Norm Fulfillment	11 (3-15)	5 (3-12)	**0.001**
Perception Vulnerability	10 (3-15)	5 (3-10)	**0.001**
Perception Severity	8 (2-10)	2 (2-7)	**<0.001**
Motivation Strength	15 (9-15)	11 (3-15)	**0.006**
Motivation Willingness	11 (3-15)	5 (3-15)	**0.002**
Socialsupport Emotionality	10 (3-15)	3 (3-13)	**0.001**
Socialsupport Appreciation	7 (2-10)	4 (2-10)	**0.008**
Socialsupport İnstrumental	12(3-15)	9 (4-15)	0.270
Empowerment Knowledge	13 (3-15)	7 (3-13)	**<0.001**
Empowerment Abilities	11 (3-15)	5 (3-15)	**<0.001**
Empowerment Desires	13 (3-15)	6 (3-15)	**<0.001**

*: Mann Whitney U test

Table 3. According to MLPNN and RBFNN models, importance values of explanatory factors

Variables	MLPNN	RBFNN
Behavior Sexualrisk	0.173	0.188
Behavior Personalhygine	0.056	0.046
Intention Commitment	0.029	0.049
Behavior Eating	0.041	0.016
Attitude Spontaneity	0.011	0.013
Intention Aggregation	0.061	0.026
Attitude Consistency	0.064	0.027
Perception Vulnerability	0.034	0.059
Norm Significantperson	0.015	0.036
Perception Severity	0.078	0.067
Norm Fulfillment	0.041	0.049
Motivation Strength	0.090	0.068
Socialsupport Appreciation	0.004	0.041
Empowerment Abilities	0.063	0.069
Socialsupport Emotionality	0.017	0.050
Motivation Willingness	0.045	0.051
Empowerment Desires	0.037	0.060
Socialsupport İnstrumental	0.035	0.031
Empowerment Knowledge	0.106	0.055
Total	1.0	1.0

DISCUSSION

Cervical cancer is a serious worldwide health problem (14). Cervical cancer affects 80% of people in developing countries. By destroying the cervix, this malignancy affects the female reproductive system. Usually, it develops without causing any symptoms at first (15). The symptoms occur in the late stages of the disease, making treatment difficult, and the condition may spread to other organs.

Modern artificial intelligence approaches, such as machine learning applications, have been widely employed and beneficial in the medical health industry in recent years. It may be of considerable aid in illness diagnosis, prognosis, and treatment, and can substantially improve the work of medical specialists, eventually improving the efficiency and quality of medical care, which has huge implications for improving medical levels, particularly in low-resource countries (16). Many cervical cancer researchers are experimenting with techniques such as machine learning. This ensures that risk variables are readily detected and examined, and that diagnostic accuracy is improved. The subject of cervical cancer classification has been the focus of a great deal of research throughout the years (17).

Nithya et al. (1) investigated cervical cancer risk factors using machine learning. There were 858 rows and 27 features in the dataset. They used the K-NN, r-part, SVM, C5.0, and Random Forest, as well as tenfold cross-validation. Parikh et al. (20) used K-NN to build a system for identifying cervical disease, selecting 25 features, 17 features, and 11 features, respectively. Tseng et al. (21) Tseng et al. utilized a dataset of 12 predictive factors from the Chung Shan Medical University Hospital Tumor Registry from 168 patients to predict cervical cancer recurrence. They compared the performance of the support vector machine (SVM), extreme machine learning (ELM), and C5.0 classifiers. According to the findings of the research, C5.0 has the greatest classification accuracy when compared to other classifiers and may also be used to pick significant independent variables (18). Machmud et al. have worked to detect cervical cancer risk using classification algorithms such as logistic regression and Naive Bayes, and behavioral theory in social sciences. They utilized data from 72 women (22 with cervical cancer and 50 without) gathered from a questionnaire administered at the Primary Health Care Hospital in Indonesia for their research. The questionnaire includes seven questions for each of four behavior-determining theories, such as planned behavior theory and protective motive theory. The study's findings revealed that the Naive Bayes approach outperforms the logistic regression method (19). Sharma utilized a clinical dataset from the International Gynecological Cancer Society that had 237 data points and 10 characteristics. Clinical diameter, uterine body, renal pelvis, and renal primary are some of the characteristics. He provided a classification model with several choices, such as rule sets, amplification, and advanced pruning, using C5.0 to characterize the stages of cervical cancer. C5.0 with pruning option 5 exhibited the greatest accuracy in diagnosing cervical cancer stage, according to the data (20). Lu et al. studied many strategies for cervical cancer advancement and established a recommended and productive assistant pattern to forecast cervical disease. The accuracy of the Decision Tree, SVM, Logistic Regression, Multilayer Perceptron and K-NN, techniques was 77.97%, 79.25%, 82.78%, 83.16%, and 82.93% respectively (21). Wu and Zhou presented a SVM based classification model in their study to diagnose cervical cancer and determine risk factors. In their studies, they used Recursive Feature Elimination (RFE) and Principal Component Analysis (PCA) techniques to both shorten the processing time and eliminate unimportant features. Thus, they identified the ten most important risk factors for the dataset with 32 features and four target variables. Since there was an imbalance problem in the data set used, the authors applied the balancing process to the data set by using the oversampling technique. Then, three SVM-based approaches were applied for the four target variables, respectively, and when the results were compared, it was shown that the SVM, PCA method was superior to the others (22). Abdoh et al. proposed a technique based on oversampling, RFE, PCA and random forests (RF) for cancer diagnosis. The simulation results show that the proposed technique can be used in the diagnosis of cervical cancer. Rayavarapu and Krishna used a deep neural network for cervical cancer prediction. Deng et al. The performance of XGBoost SVM and RF techniques in cervical cancer classification was investigated. As a result of the study, it has been seen that XGBoost and RF techniques have better performance than SVM (3). Hyeon et al. used a pre-trained convolutional neural network (CNN) and several machine learning classifiers as feature extractors to classify cell images as normal and abnormal. Logistic Regression, Random Forest, AdaBoost and SVM, which are machine learning classifiers, were used in the study. Studies were carried out in MATLAB software. At the end of the studies, the support vector machine achieved the highest performance with an F1 score of 78% (23).

The goal of this research was to evaluate classification predictions using MLPNN and RBFNN from ANN models using an open-source "Cervical Cancer Behavior Risk" dataset.

An artificial neural network is a mathematical model that solves classification and prediction problems by using the control and functional components of artificial neural networks. Input and output layers, as well as hidden layers that change input to output, make up neural networks. The architecture of an artificial neural network may be constructed in two stages: training and testing, when it is utilized to forecast any illness. The weights of the connections between neurons are fixed once the ANN model has been trained with the given dataset. Second, the model under consideration is validated in order to classify a new data set. Several parameters are used to assess the performance of the produced models (24).

In this research, the RBFNN model performed better than the MLPNN model in predicting the classification of cervical cancer according to performance criteria. During the test stage, the performance measures accuracy, specificity, AUC, negative predictive value, and positive predictive value obtained from the RBFNN method were 92.3, 100.0, 0.965, 91.6, and 100.0 respectively. The three most significant risk variables related with cervical cancer were assessed in the RBFNN model as behavior sexual risk, empowerment abilities, and motivation strength.

CONCLUSION

As a result, using multi-layer perceptron and radial-based artificial neural network models, this framework estimates various factors (explanatory variables) that may be related to cervical cancer. In light of the obtained results, the applicability of artificial intelligence methods in the classification problem of interest is demonstrated. These models have established the significant levels of potential cervical cancer risk variables for preventive medication.

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Author Contributions:

Concept: İBÇ, ZK. Design: İBÇ, ZK. Literature search: İBÇ, ZK. Data Collection and Processing: İBÇ, ZK. İB. Analysis or Interpretation: İBÇ, ZK. Written by: İBÇ, ZK.

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