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Comparison of Performances of Associative Classification Methods for Cervical Cancer Prediction: Observational Study

Rahim Ağzı Kanseri Tahminî İçin İlişkisel Sınıflandırma Yöntemlerinin Performanslarının Karşılaştırılması: Gözlemsel Çalışma

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ABSTRACT Objective: Associative classification is a method that generates a rule-based classifier in a categorical data set. The main purpose of the associative classification is to create classification models with high performance and, in addition, to improve interpretability thanks to the rules it creates. In this study, it is aimed to classify, predict cervical cancer with the methods of relational classification and to determine the most important parameters and relational rules associated with the disease. **Material and Methods:** In the study, regular class association rules (RCAR) and classification based on associations (CBA) methods were applied to the open access data set named "Cervical Cancer Behavioral Risk Data Set" and the results were compared. In order to separate the numerical variables in the data set, Boruta feature selection method was applied to determine the most important features about Ameva and cervical cancer. The performances of the created relational classification models were evaluated with accuracy, balanced accuracy, sensitivity, specificity, Matthews correlation coefficient (MCC), G-mean, diagnostic accuracy, Youden's index, positive predictive value, negative predictive value and F1-score criteria. **Results:** According to CBA model results, sensitivity is 100%, specificity 98%, accuracy 98.6%, balanced accuracy 99%, Youden's index 98%, MCC 96.7%, diagnostic accuracy 98.6%, G-mean 97.7%, negative predictive value 1%, positive predictive value 95.5%, and F1 score 97.7%. According to RCAR model results, sensitivity is 90.5%, specificity 98%, accuracy 95.8%, balanced accuracy 94.3%, Youden's index 88.5%, MCC 89.8%, diagnostic accuracy 95.8%, G-mean 95.6%, negative predictive value 96.2%, positive predictive value 95%, and F1 score 92.7%. **Conclusion:** When the results are examined, it can be said that the CBA model is more successful in classifying cervical cancer compared to the RCAR model. In addition, the relational classification models created in this study and the rules obtained regarding the disease are promising in terms of their use in early diagnosis and preventive medicine practices for cervical cancer.

Keywords: Cervical cancer; regularized class association rules; classification based on association rules; associative classification methods

ÖZET Amaç: İlişkili sınıflandırma, kategorik bir veri kümesinde kural tabanlı bir sınıflandırıcı oluşturan bir yöntemdir. İlişkisel sınıflandırmanın temel amacı, yüksek performanslı sınıflandırma modelleri oluşturmak ve ayrıca oluşturduğu kurallar sayesinde yorumlanabilirliği artırmaktır. Bu çalışmada, rahim ağzı kanserinin ilişkisel sınıflandırma yöntemleri ile serviks kanserinin sınıflandırılması, tahmin edilmesi ve hastalıkla ilişkili en önemli parametrelerin ve ilişkisel kuralların belirlenmesi amaçlanmıştır. **Gereç ve Yöntemler:** Çalışmada "Rahim Ağzı Kanseri Davranışsal Risk Veri Seti" adlı açık erişim veri setine düzenli sınıf ilişkilendirme kuralları [regular class association rules (RCAR)] ve ilişki kurallarına dayalı sınıflandırma [classification based on association (CBA)] yöntemleri uygulanmış ve sonuçlar karşılaştırılmıştır. Veri setindeki sayısal değişkenleri ayırmak amacıyla Ameva ve rahim ağzı kanseri ile ilgili en önemli özellikleri belirlemek için Boruta özellik seçme yöntemi uygulanmıştır. Oluşturulan ilişkisel sınıflandırma modellerinin performansları; doğruluk, dengeli doğruluk, duyarlılık, özgüllük, Matthews korelasyon katsayısı [Matthews correlation coefficient (MCC)], G-ortalama, tanısal doğruluk, Youden indeksi, pozitif tahmin değeri, negatif tahmin değeri ve F1 skor kriterleri ile değerlendirildi. **Bulgular:** CBA model sonuçlarına göre duyarlılık %100, özgüllük %98, doğruluk %98,6, dengeli doğruluk %99, Youden indeksi %98, MCC %96,7, tanısal doğruluk %98,6, G-ortalama %97,7, negatif tahmin değeri %1, pozitif tahmin değeri %95,5 ve F1 puanı %97,7'dir. RCAR model sonuçlarına göre duyarlılık %90,5, özgüllük %98, doğruluk %95,8, dengeli doğruluk %94,3, Youden indeksi %88,5, MCC %89,8, tanısal doğruluk %95,8, G-ortalama %95,6, negatif tahmin değeri %96,2, pozitif tahmin değeri %95 ve F1 puanı %92,7. **Sonuç:** Sonuçlar incelendiğinde, CBA modelinin RCAR modeline göre rahim ağzı kanserini sınıflandırmada daha başarılı olduğu söylenebilir. Ayrıca bu çalışmada oluşturulan ilişkisel sınıflandırma modelleri ve hastalığa ilişkin elde edilen kurallar, rahim ağzı kanserine yönelik erken tanı ve koruyucu hekimlik uygulamalarında kullanılması açısından umut vericidir.

Anahtar kelimeler: Rahim ağzı kanseri; düzenli sınıf birleştirme kuralları; ilişkilendirme kurallarına göre sınıflandırma; ilişkisel sınıflandırma yöntemleri

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Cervical cancer is the third most common type of cancer in women, with approximately 275,100 deaths and 529,800 new cases worldwide. More than 85% of cervical cancers occur in developing countries. Cervical cancer cases could potentially be prevented due to the slow progression of the disease, its cytologically identifiable precursors, and the availability of effective treatment methods if diagnosed early. One of the major risk factors in the development of this cancer is the human papillomavirus (HPV).[1,2]

The Papanicolaou smear test screening and HPV vaccine are frequently used to prevent the disease. Although screening is an opportunity to prevent cervical cancer in women, the scope of screening remains low due to the lack of basic knowledge about screening, lack of awareness, uncomfortable with the procedure, and not knowing where to go for the Papanicolaou smear test. HPV vaccine does not provide complete protection because only some HPV types are included in vaccines and the long-term efficacy of vaccines has not yet been determined. Cervical cancer treatment is very limited, so primary and secondary prevention methods provide the best options for this health problem. Thus, primary prevention of cervical cancer through culturally informed personal health behavior becomes important, especially as sexual behavioral factors increase the risk of this cancer behavior preservation, which is the primary prevention for decreasing mortality in cervical cancer, is known to be cost-effective.[3,4]

Machine learning is a field that investigates the work and construction of algorithms that can learn as a structural function and make predictions over data.[5,6] Association rules (AR), which is one of the machine learning methods, is frequently used in the field of medicine because it can determine the risk factors for the disease with the help of certain criteria and can be interpreted easily. ARs express the formation of patterns between variables in the data set with certain probabilistic criteria.[7,8] Associative classification combines AR and classification methods to create a model with high predictive power. Associative classification methods generate highly accurate classifier models. Besides, the main advantage of relational classifiers is the interpretation of results. Associative classification aims to prune unnecessary rules in the set of rules, combine and improve these rules to create a classifier.[9,10]

This study aims to create a classification model that predicts the disease with high accuracy by using the AR method for early diagnosis and treatment of cervical cancer based on behavioral risk factors.

MATERIAL AND METHODS

DATASET

The open-access dataset called "Cervical Cancer Behavior Risk Data Set" was obtained from the University of California Irvine machine learning repository.[11] The dataset consists of 72 samples examined for cervical cancer with 18 predictors and one output variable. Of the samples, 50 (69.45%) were defined as without cervical cancer, and 22 (30.55%) were defined as with cervical cancer.

DATA PRE-PROCESSING

Since the regular class association rules (RCAR) and classification based on associations (CBA) algorithms works on categorical data, firstly, the numerical variables in the data set were categorized with the Ameva algorithm, which maximizes the dependency relationship between class tags. Then, a feature selection algorithm was applied to Boruta to determine the features most associated with cervical cancer. Boruta is a random forest-based feature selection method that enables the selection of important and non-important variables from a data set in an unbiased and stable way with the shadow variables and iterative structure it adds to the data set. An associative classification model was created with the RCAR and CBA algorithm after feature selection. While creating rules with RCAR and CBA, the minimum support value was set to 0.2 and the minimum confidence value to be 0.5.

ASSOCIATIVE CLASSIFICATION

The main purpose of associative classification is to integrate classification methods and AR to create class AR (CARs). AR mining is usually created in 2 steps. The first step is to reveal all frequently used item sets that are sets of items that meet the minimum threshold of support criteria. The second stage is that all AR that meet the trust criterion threshold are created from the sets of items revealed in the first stage. The first stage is often more important than the second stage and can be computationally expensive for large databases.[12,13]

CLASSIFICATION BASED ON ASSOCIATIONS

CBA consists of 2 parts that combine classification and AR. The first part, called association rule generation (CBA-RG), is an adaptive version of Apriori used to find CARs. The second part of CBA, called the classifier building (CBA), is part that builds the classifier based on CARs found using CBA-RG. Rules that do not improve the accuracy of the classifier are discarded in relational classification. The classifier creates rules that are incremented by a default class and not thrown. Therefore, associative classification methods provide higher estimation accuracy than traditional methods.[14,15]

REGULARIZED CLASS ASSOCIATION RULES ALGORITHM FOR CLASSIFICATION

RCAR is an algorithm that creates a classification model based on AR that can only be applied in categorical data sets. The RCAR algorithm miners a set of rules according to predetermined thresholds of minimum support and trust criteria (s, c). Then Lasso's regulated logistic regression analysis is applied to the rule space to create a model predicting the conditional probability of the class variable. The rules kept in the model include meta-rules, which are one-way associations. With Lasso regularization using found meta-rules, selected CARs are organized and visualized in the first step of pruning. In the RCAR algorithm, CARs are revealed using a method similar to Apriori, and the rule pruning problem is solved by arranging the lasso. An optional pruning step can be performed on the basis of an in-depth analysis of established rules and meta-rules.[16,17]

PERFORMANCE EVALUATION CRITERIA

The confusion matrix used to calculate the performance criteria of the classification models is given in Table 1.

The confusion matrix used in the calculation of the performance criteria of the classification models is given in Table 1 and the formulas for the classification performance criteria are given in Table 2.

TABLE 1: Confusion matrix for calculating performance metrics.

		Real		
		Positive	**Negative**	**Total**
Predicted	Positive	True positive	False negative	**TP+FP**
	Negative	False positive	True negative	**FN+TN**
	Total	**TP+FP**	**FN+TN**	**n**

TP: True positive; FP: False positive; FN: False negative; TN: True negative.

TABLE 2: Formulas for calculating performance criteria.

Metric	**Formula**
Accuracy	(TP+TN)/n
Balanced accuracy	[[TP/(TP+FN)]+[TN/(FP+TN)]]/2
Sensitivity	TP/(TP+FN)
Specificity	TN/(FP+TN)
Positive predictive value	TP/(TP+FP)
Negative predictive value	TN/(TN+FN)
F1-score	(2*TP)/(2*TP+FP+FN)

TP: True positive; TN: True negative; FN: False negative; FP: False positive.

RESULTS

As a result of variable selection with Boruta method; behavior sexual risk, behavior personal hygiene, norm significant person, norm fulfillment, perception vulnerability, perception severity, motivation strength, motivation willingness, social support emotionality, social support appreciation, social support instrumental, empowerment knowledge, empowerment abilities, empowerment desires, intention aggregation, and intention commitment parameters were selected and included in the CBA and RCAR models. The values of performance criteria for the CBA and RCAR models created are shown in Table 3.

TABLE 3: Values of CBA and RCAR models performance criteria.

Metric	CBA model		RCAR model	
	Prediction value	95% CI	Prediction value	95% CI
Accuracy	0.986	0.959-1	0.958	0.912-1
Balanced accuracy	0.99	0.967-1	0.943	0.889-0.996
F1-score	0.977	0.942-1	0.927	0.867-0.987
MCC	0.967	0.926-1	0.898	0.828-0.968
G-mean	0.977	0.942-1	0.956	0.908-1
Sensitivity	1	0.839-1	0.905	0.696-0.988
Specificity	0.98	0.896-1	0.98	0.896-1
Diagnostic accuracy	0.986	0.925-1	0.958	0.883-0.991
Youden's index	0.98	0.734-1	0.885	0.592-0.988
Positive predictive value	0.955	0.772-0.999	0.95	0.751-0.999
Negative predictive value	1	0.929-1	0.962	0.868

CBA: Classification based on associations; RCAR: Regular class association rules; CI: confidence interval; MCC: Matthews correlation coefficient.

According to the results of the CBA model, sensitivity is 100%, specificity 98%, accuracy 98.6%, balanced accuracy 99%, Youden's index 98%, Matthews correlation coefficient (MCC) 96.7%, diagnostic accuracy 98.6%, G-mean 97.7%, negative predictive value 1%, positive predictive value 95.5%, and F1 score 97.7%.

According to the results of the RCAR model, sensitivity is 90.5%, specificity 98%, accuracy 95.8%, balanced accuracy 94.3%, Youden's index 88.5%, MCC 89.8%, diagnostic accuracy 95.8%, G-mean 95.6%, negative predictive value 96.2%, positive predictive value 95%, and F1 score 92.7%.

Table 4 shows the AR used in the RCAR model.

TABLE 4: Association rules used by the RCAR algorithm.

Left-hand side rules	Right-hand side rules	Support	Confidence	Frequency
{perception_severity=[2,5)}	{class=cervical cancer}	0.278	0.513	20
{perception_severity=[2,5), empowerment_desires=[3,9.5)}	{class=cervical cancer}	0.208	0.938	15
{norm_fulfillment=[3,10.5), empowerment_desires=[3,9.5)}	{class=cervical cancer}	0.208	0.938	15
{perception_severity=[2,5), empowerment_abilities=[3,7.5)}	{class=cervical cancer}	0.222	0.941	16
{norm_fulfillment=[3,10.5), empowerment_abilities=[3,7.5)}	{class=cervical cancer}	0.222	0.941	16
{perception_severity=[2,5), socialsupport_emotionality=[3,8.5)}	{class=cervical cancer}	0.236	0.895	17
{norm_fulfillment=[3,10.5), socialsupport_emotionality=[3,8.5)}	{class=cervical cancer }	0.236	0.895	17
{perception_vulnerability=[3,10.5), perception_severity=[2,5)}	{class=cervical cancer}	0.278	0.513	20
{behavior_sexualrisk=[10,Inf], motivation_strength=[15, Inf]}	{class=no cervical cancer}	0.361	0.897	26
{behavior_sexualrisk=[10,Inf], motivation_willingness=[6,15)}	{class=no cervical cancer}	0.514	0.86	37
{perception_vulnerability=[3,10.5),empowerment_knowledge=[3,8.5), empowerment_abilities=[3,7.5)}	{class=cervical cancer}	0.208	0.833	15
{perception_vulnerability=[3,10.5),perception_severity=[2,5), empowerment_desires=[3,9.5)}	{class=cervical cancer}	0.208	0.938	15
{norm_fulfillment=[3,10.5),perception_vulnerability=[3,10.5), empower-ment_desires=[3,9.5)}	{class=cervical cancer}	0.208	0.938	15

RCAR: Regular class association rules.

Examining Table 4, if perception severity=(2,5) and empowerment desires=(3,9.5) the probability of having cervical cancer is 93.8%. Similarly, if behavior sexual risk=[10,Inf] and motivation strength=[15,Inf], the probability of not having cervical cancer is 89.7%. If norm fulfillment=(3,10.5) and empowerment abilities=(3,7.5)}, the probability of cervical cancer is 94.1%.

Table 5 shows the AR used in the CBA model.

TABLE 5: Association rules used by the CBA algorithm.

Left-hand side rules	Right-hand side rules	Support	Confidence	Frequency
{empowerment abilities=[7.5,15), empowerment desires=[9.5,15)}	{class=no cervical cancer}	0.264	1	19
{empowerment abilities=[7.5,15), intention aggregation=[10, Inf]}	{class=no cervical cancer}	0.25	1	18
{behavior_sexualrisk=[10, Inf], social support instrumental=[5.5,15), empowerment desires=[9.5,15)}	{class=no cervical cancer}	0.25	1	18
{perception severity=[10, Inf]}	{class=no cervical cancer}	0.222	1	16
{motivation strength=[15, Inf], empowerment abilities=[7.5,15)}	{class=no cervical cancer}	0.222	1	16
{perception vulnerability=[10.5,15)}	{class=no cervical cancer}	0.208	1	15
{norm fulfillment=[10.5,15), norm significant person=[5, Inf]}	{class=no cervical cancer}	0.208	1	15

CBA: Classification based on associations.

Examining Table 5, if empowerment abilities=[7.5,15), and empowerment desires=[9.5,15) the probability of not having cervical cancer is 100%. Similarly, if norm fulfillment=[10.5,15), and norm significant person=[5,Inf], the probability of not having cervical cancer is 100%.

DISCUSSION

Cervical cancer is one of the most common types of cancer in women. Although it is mostly seen in middle-aged and elderly women, it can occur at any age. Cervical cancer is among the early detectable and preventable cancers with healing potential. When diagnosed and treated early, the recovery rate is high; also, complete recovery can be achieved.[1]

Machine learning and data mining techniques are used to assist doctors in diagnosing the disease early.[18] One of the most important of these techniques is the AR methods. AR are often used in descriptive data analysis to find trends and relationships in data. Relationships between objects and/or groups of objects can be specified. Later, these rules can be used in decisions and definitions to be made.[7,19] Associative classification methods, on the other hand, combine AR and classification methods, giving high accuracy results compared to traditional methods and are easy to interpret.[12,20]

In this study, the RCAR and CBA model was created for cervical cancer behavior risk factors data set. First, different risk factors that may be associated with the diagnosis of cervical cancer were selected by the Boruta feature selection method. It is thought that the variables selected by the Boruta method will guide healthcare professionals in the diagnosis/treatment of the disease and in preventive medicine. In this way, deaths can be prevented by early diagnosis and treatment of the disease. Then, cervical cancer is estimated with the associative classification model, and AR are found.

In a study in which the same data set was used in the literature, Naïve Bayes and logistic regression methods were used and an accuracy rate of 91.67% and 87.5%, respectively, was obtained. In the present study, RCAR model predicted cervical cancer with 95.8% accuracy and CBA model 98.6% accuracy.[11] As a result, it can be said that the models created are more successful in predicting cervical cancer than in the study in the literature. The results of the associative classification models used in the present study are easier to interpret and understand than the methods used in the study in the literature. In addition, it is clear that CBA method, one of the associative classification models created in the study, has a higher performance than the RCAR method.

CONCLUSION

Cervical cancer classes (cervical cancer, not cervical cancer) were estimated based on the most important risk factors using artificial intelligence approaches. The proposed algorithm, CBA, performs better in cervical cancer classification compared to the RCAR model. In addition, it is thought that the AR obtained for cervical cancer risk factors will help healthcare professionals in the follow-up of the disease.

Source of Finance

During this study, no financial or spiritual support was received neither from any pharmaceutical company that has a direct connection with the research subject, nor from a company that provides or produces medical instruments and materials which may negatively affect the evaluation process of this study.

Conflict of Interest

No conflicts of interest between the authors and/or family members of the scientific and medical committee members or members of the potential conflicts of interest, counseling, expertise, working conditions, share holding and similar situations in any firm.

Authorship Contributions

Idea/Concept: *Fatma Hilal Yağın, Burak Yağın, Ahmet Kadir Arslan, Cemil Çolak;* ***Design:*** *Fatma Hilal Yağın, Burak Yağın, Ahmet Kadir Arslan;* ***Control/Supervision:*** *Fatma Hilal Yağın, Cemil Çolak;* ***Data Collection and/or Processing:*** *Fatma Hilal Yağın, Ahmet Kadir Arslan;* ***Analysis and/or Interpretation:*** *Fatma Hilal Yağın, Burak Yağın, Cemil Çolak;* ***Literature Review:*** *Fatma Hilal Yağın, Cemil Çolak;* ***Writing the Article:*** *Fatma Hilal Yağın, Burak Yağın, Cemil Çolak;* ***Critical Review:*** *Ahmet Kadir Arslan, Cemil Çolak;* ***References and Fundings:*** *Cemil Çolak;* ***Materials:*** *Fatma Hilal Yağın, Cemil Çolak.*

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