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Prediction of The Patients at Risk for Development Hematoma after Percutaneous Coronary Angiography: A Nursing Decision Support Model Pilot Study

Perkütan Koroner Anjiyografi Sonrası Hematom Gelişimi Riski Olan Hastaların Tahmini: Hemşirelik Karar Destek Modeli Pilot Çalışması

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ABSTRACT

The study aimed to develop a nursing clinical decision support model using the machine learning method, which is one of the important fields today, to identify patients with risk of hematoma development after percutaneous coronary intervention and to help plan appropriate nursing interventions. In this study, the data of 100 patients with myocardial infarction was used in the development of the decision support model. R open-source programming language was used for statistical analysis of the data and the random forest method, one of the machine learning methods was used for the development of the model. The result of this pilot study, a nursing decision support model with a sensitivity of 69% and a specificity of 64% was developed with the Random forest method using 24 features regarding the demographic, laboratory, and percutaneous coronary intervention procedures of the patients.

Keywords: Artificial Intelligence, Coronary Angiography, Decision Support Systems, Machine Learning, Nursing Informatics,

ÖZET

Çalışmada, günümüzün önemli alanlarından biri olan makine öğrenmesi yöntemini kullanarak, perkütan koroner girişim sonrası hematom gelişme riski taşıyan hastaların belirlenmesi ve uygun hemşirelik girişimlerinin planlanmasına yardımcı olacak bir hemşirelik klinik karar destek modelinin geliştirilmesi amaçlandı. Bu çalışmada karar destek modelinin geliştirilmesinde 100 miyokard enfarktüsü hastasının verileri kullanıldı. Verilerin istatistiksel analizinde R açık kaynak programlama dili kullanılmış olup, modelin geliştirilmesinde makine öğrenmesi yöntemlerinden biri olan rastgele orman yöntemi kullanılmıştır. Bu pilot çalışmanın sonucunda hastaların demografik, laboratuvar ve perkütan koroner girişim işlemlerine ilişkin 24 özelliği kullanarak Rastgele orman yöntemiyle %69 duyarlılığa ve %64 özgüllüğe sahip bir hemşirelik karar destek modeli geliştirildi.

Anahtar Kelimeler: Hemşirelik Bilişimi, Karar Destek Sistemi, Koroner Anjiyografi, Makine Öğrenmesi, Yapay Zeka

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INTRODUCTION

Percutaneous coronary intervention (PCI) is an invasive procedure that is widely used in the diagnosis and treatment of coronary artery disease (CAD), which occupies an important position among chronic diseases nowadays and reduces the morbidity and mortality of cardiovascular diseases.[1]

The catheter (sheath) is placed in the femoral, radial, brachial and axillary arteries via the percutaneous route and is removed after the procedure is completed. When the PCI procedure is completed, the sheath(s) are removed and pressure must be applied to the artery until haemostasis is achieved.[2] While some of the patients are discharged within 24 hours after PCI procedure, some face serious, life-threatening vascular complications after it. The incidence of vascular complications is usually 2-6% according to the American Heart Association (AHA) report, and this rate is increasing gradually.[3] A meta-analysis reported that the prevalence of acces site bleeding was 11.2%.[4]

Vascular complications often include bleeding, hematoma, ecchymosis, pseudoaneurysm, arteriovenous fistula, and retroperitoneal hematoma.[2, 5] Most of these vascular complications develop in the femoral artery region that requires large-bore sheath access, performed predominantly via the transfemoral.[2] Although the ESC guideline recommends the use of radial artery as a catheter intervention site, which reduces the risk of bleeding, vascular complications and mortality , femoral intervention continues to be used in complex cases, especially when larger lumen catheters are required.[2, 6, 7] The rate of vascular complications requiring surgical intervention is reported between 0.2% and 9%, causing serious discomfort to the patient, extending the length of hospital stay, causing additional diagnosis and treatment procedures, increasing hospital cost, and more importantly increasing mortality.[8] Besides, these complications take a long time to heal.[9]

Significant bleeding in the femoral artery region may be evident by the complaint of local pain and the finding of a large hematoma.[7] A hematoma is a blood accumulation located in the soft tissue and is identified by local hardness, swelling, and pain. Also, it is considered the most common vascular intervention complication and is one of the complications requiring severe blood transfusion at the femoral artery entry site.[3, 5] Recent studies have offered evidence that bleeding, post PCI, is dangerous, therefore it is necessary for all health care providers to take all measures to decrease it.[4] In a study of 37,866 Australian patients undergoing PCI patients, it was mentioned that major bleeding is an uncommon but potentially fatal PCI complication and was independently.[10] Among the factors that cause vascular problems during or after the PCI procedure are the use of anticoagulant drugs, the characteristic and stay time of the catheter in the femoral artery, catheter removal technique, gender, body mass index, age, chronic disease status, the experience of the team performing the procedure, type of intervention planned and quality of nursing care provided.[3, 8] Increasing number of catheterization, developing pharmaceutical industry and technology show that nurses have a significant role in the prevention of vascular complications in patients after cardiac catheterization. International evidence-based guidelines have been created to ensure the medical management of the PCI. It is noteworthy that the role of nurses and the impact of nursing interventions are rarely described and analyzed in these guidelines.[1] Nursing care practices are priority and necessary for the prevention of vascular complications.[2] Nursing care protocols and practices are very few and still under development to provide quality nursing care .[1] In most of the studies, pain developed in patients after PCI and ecchymosis / hematoma, different methods of sheath removal practices following PCI, changing body position after PCI and post-rest ambulation time were investigated [11-16]. However, no predictive study has been performed on PCI procedure for the risk of developing femoral hematoma in patients. Therefore, this study aimed to develop an assistive Nursing Decision Support Model (NDSM) in the process of identifying patients with risk of hematoma development after PCI and planning appropriate nursing interventions for these patients.

MATERIAL AND METHOD

Study Design

The data of the study were obtained prospectively, analyzed retrospectively. Random forest method, one of the machine learning methods, was used in the development of the decision support model.

Data Set Description

The data used in the developed system was collected by researchers from patients treated in the coronary intensive care unit. The hospital where the research was conducted serves the Eastern Black Sea region on cardiovascular diseases, and over 6 thousand angiographies are performed annually in the hospital. The data were obtained from hospitalized patients in the intensive care unit with the diagnosis of myocardial infarction who underwent PCI between August 2011 and January 2012, prospectively. The data set used in the study consisted of information from 100 patients; 50 patients who developed hematoma after PCI and 50 who did not. The inclusion criteria for the patients were having a coronary intervention site femoral artery. Data of patients which taking thrombolytic and glycoprotein 2b/3a medication, and having any previously known coagulation disorders were excluded since they are factors that can contribute to the development of the hematoma and have the potential to directly affect developed model prediction results.

Patient data were obtained by analyzing biochemistry laboratory test results, epicrisis reports, angiography reports and nurse observation forms. Parameters related to hematoma development risk after PCI procedure were determined by examining the literature studies [3, 8]. These parameters are patient information (age, gender, height, weight, hypertension status, diabetes status), laboratory values before PCI Procedure (Erythrocyte (RBC), Hemoglobin (HGB), White Blood Cell (WBC), Thrombocyte (PLT), Glucose, Sodium (Na), Potassium (K), Calcium (Ca), Hematocrit (Hct), Aptt(Activated partial thromboplastin time) , Pt (Prothrombin time), INR, PCI Features (PCI Procedure Time (min), Catheter thickness, Femoral catheter access side), Anticoagulant/Antiplatelet Therapy (Heparin dose, Plavix use). The development of the hematoma status of patients was obtained by scanning nurse observation records.

Statistical Procedures

R studio open source statistical programming language was used for the analysis of the data set and development of the prediction model. Descriptive statistics of the parameters of the data set were analyzed using functions such as R program "summary", "summarytools::freq", and "describe". Random Forest method, one of the machine learning methods, was used to develop the model, and R "randomForest" and "caret" packages were used.

Model Development

Machine learning is a field of study that deals with the development of computer algorithms to turn data into smart actions. In the field of health, there are various studies using machine learning for many purposes such as classification of diseases, mortality and morbidity prediction, risk prediction, risk of developing chronic disease, appropriate drug dose calculation, and appropriate treatment. Machine learning methods can basically be examined in two groups as supervised and unsupervised learning. Supervised learning method, also known as learning from examples, is a method that produces an output by learning from the examples in the data separated as a training set. Supervised learning methods can be used for classification and regression problems.[17] Random forest is one of the supervised learning methods and is based on combining several random decision tree models and performs estimations by averaging and yields good results even when the number of features in the data set is high. Random forest, one of the automatic classification algorithms that can learn and predict data by creating a model in the form of input-output relationships of variables, is a method based on the decision tree principle and can be used to solve many problems such as feature selection, classification, regression. Compared to other methods, random forest stands out with its advantages such as being effective in large-scale data, not having an overfitting problem, being able to use both numerical and categorical variables, and being easily applied in multi-class problems.[18]

The size of the training and test sets, incorrect classification (overfitting, under fitting) or class distribution play an important role in the performance of a model to be used. There are methods such as holdout and cross validation developed to prevent these problems from negatively affecting learning.[19] In this study, the holdout method was used, in which the data set was divided into two as training and test data set.

The dataset was randomly split into two sets. Specifically, 70% of the 100 data was allocated to the training set, while the remaining 30% was designated for the test set. The variables provided in Table 1 were used as input vectors for the model, resulting in the prediction of hematoma development (Post-PCI hematoma status) as output.

Evaluation of The Prediction Model

Sensitivity, Specificity and AUC (Area Under Curve) values are among the important evaluation criteria for the success of the decision support models. The prediction sensitivity of a model measures the proportion of correctly classified positive samples. That is while the sensitivity value is obtained by the proportion of positives (TP) that the model correctly classifies to all positives (TP+FN) in the real state, specificity value is obtained by the proportion of correctly classified negative samples (TN) to all negatives (TN + FP).

Ethical Aspect of Research

The ethical permission was obtained from the Ethics Committee (number: 24237859-404/ date: 03.07.2020).

FINDINGS AND DISCUSSION

The analysis results are given in Table 1. The study was conducted on a total of 100 patients, 21 females and 79 males. The number of patients who developed hematoma after PCI is 50, and the number of patients who do not develop is 50. It was determined that patients age mean value was 61.9 ± 11.8, weight mean value was 79.5 ± 13.7 kg and height mean value was 167.6 ± 7.33cm. 11% of patients had diabetes, 43% had a history of hypertension and 88% of the patients used 7f catheter during PCI, while 12% used 6f. The mean value of duration of PCI procedure was 57.1± 28. The laboratory findings were obtained before the procedure and the mean values of Hemoglobin, White blood cell, Thrombocyte, Erythrocyte, Hematocrit and Glucose that were 13.9 ± 1.3, 9.7 ± 2.6, 220 ± 45, 4.7 ± 1.3, 42.6±4, 125± 44, respectively. Among the coagulation factors, mean value of INR was 1.2± 0.2, mean value of Aptt was 44±37and mean value of Pt was 15.5±13.

Table 1. Descriptive Statistics of The Dataset

Categorical Variables (n=100)	n (%)
Gender	
Female	79 (79)
Male	21 (21)
Presence of hypertension	
Yes	43 (43)
No	57 (57)
Presence of diabetes	
Yes	11 (11)
No	89 (89)
Thickness of catheter	
7f	88 (88)
6f	12 (12)
Use of plavix	
Yes	40 (40)
No	60 (40)
Post-PCI hematoma status	
Yes	50 (50)
No	50 (50

Table 1 (Continued)

Numerical Variables	Mean±SD	Min-Max
Hemoglobin (g/dl)	13.9±1.3	10.3-16.8
White blood cell (10^3/mm³))	9.7±2.6	3.8-15.6
Thrombocyte (10^3/mm³)	220±45	150-346
Erythrocyte (10^{12}/mm³)	4.7±1.3	3.3-14.1
Glucose (mg/dl)	125±44	75-352
Sodium (mmol/L)	135.6±3.6	127-143
Potassium (mmol/L)	4.2±0.5	3.3-5.7
Calcium (mg/dl)	9.2±0.7	7.1-10.8
Hemotocrit (%)	42.6±4	31.8-51.5
Aptt (sn)	44±37	20-180
Pt (sn)	15.5±13	1.2-130
INR	1.2±0.2	1-2.5
Age	61.9±11.8	21-83
Time of PCI procedure (min)	57.1±28.1	20-190
Heparin_dose (IU)	8285±2108	5000-12500
Height (cm)	167.6±7.33	150-190
Weight (kg)	79.5±13.7	50-123

Model Development Process

By using the R, 100 data were divided into two sets, 70 of which were training set and 30 of which were test set. Distribution of train and test set were given in Table 2.

Table 2. Distribution of train and test sets

	Train Set	Test Set
Hematoma Development		
Yes	34	16
No	36	14
Total	70	30

The model realizes the learning by using the training set that is determined before the class labels. Then, model prediction performance was evaluated on the test set which had no class label and had never learned. Random Forest method, one of the machine learning methods, was used to develop the model, and R "randomForest" and "caret" packages were used. In this study, the success of the developed risk prediction model for hematoma after PCI using the training set was evaluated on 30 test data. Confusion matrix showing the prediction results of the developed model is given below.

Table 3. Confusion matrix of the model on test set

Real State	Prediction of the Model		
	Hematoma Development	**No Hematoma Development**	Total
Hematoma Development	11(TP)	5(FN)	16
No Hematoma Development	5 (FP)	9 (TN)	14
Total	16	14	**30**

Table 3. shows that the model correctly classified 11 of 16 patients who developed hematoma after PCI. Besides, 9 of 14 patients who did not develop a hematoma in real condition were also correctly classified.

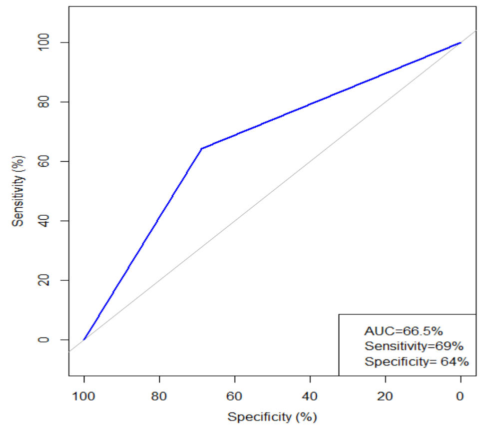

Figure 1. ROC Curve of The Prediction Model

As a result, as seen in Figure 1. Nursing decision support model with 69% sensitivity and 64% specificity values was developed and AUC value was found as 66.5%.

Clinical decision support systems are defined as systems that provide evidence-based recommendations by linking evidence and practice. Specific to the field of health, there are clinical decision support systems that were developed and used for the diagnosis, classification of diseases, and determination of appropriate treatments and risk groups. When the literature studies are examined, although there are models developed for the prediction of heart diseases or risc factors, a prediction model to determine the patients with hematoma development risk after PCI developed by using machine learning methods has not been found. Dauwan et al., an 87% accurate model was developed in the dementia and alzheimer's classification using the random forest method.[20] In another study published in 2009, an artificial neural network model was created for subdural hematoma prediction. The model yielded 88% sensitivity and 68% specificity results on 75 patient data.[21]. 89% sensitivity and 88% specificity values were obtained using the Naive Bayes method in a machine learning study that was developed to estimate the outcome of coronary angiography.[22] In a study published in 2016, developed machine learning algorithms for the identification of peripheral artery disease and the prognostication of mortality risk. It was seen that machine-learned models outperformed regression models both for the identification of patients with peripheral artery disease (AUC value: 0.87) and for the prediction of mortality (AUC value:0.76).[23]

There are a limited number of studies on nursing decision support systems. Known as COMMES (Creighton Online Multiple Modular Expert System), the first decision support system in the field of nursing was developed to help nurses in care planning.[24] In a study published in 2011, the relationship between the decision support system called APACHE III and the real situation of the patients was investigated, and a significant relationship was found r .95 ($p <0.05$).[25] APACHE III is used to support clinicians in the decision-making phase of patient transfer and triage, survival treatments, ventilation, hemodialysis, or discontinuation of some treatments Another decision support system N-CODES was designed to help new nurses make clinical decisions.[26] In a study published in 2014, a computer-aided decision support model was developed to assist nurses in the assignment of patients, and as a result, it significantly saved time in the nurse-patient assignment.[27] Studies show that nurses have used various decision support systems in the decision-making process and evaluated these systems positively.[18] With their active role in the primary care of patients, nurses first evaluate the patient, plan the care, apply appropriate nursing interventions, and evaluate the outcome of care. At this stage, especially nurses providing care for risky patient groups must plan appropriate nursing interventions, so the patient needs to be diagnosed accurately and quickly. In this study, the pilot NDSM was developed to identify patients at risk of developing hematoma after PCI which is thought to increase the quality of care in the clinic. As well as having acceptable sensitivity and specificity values, this NDSM is a unique study using machine learning methods to identify patients at risk of developing hematoma after PCI. It is thought that the use of NDSM by nurses who provide care in many areas will be useful and effective in diagnosing the patient. It is seen that these studies in the field of health are directed to clinical guidelines with NDSM systems and to improve the quality of medical care.

Limitations

The limitation of the research is that the study was conducted in a single research center in Turkey, and only 100 patient data can be used because the nursing practice records were not recorded in the information systems.

CONCLUSION AND RECOMMENDATIONS

In this study, a nursing decision support pilot model was developed by using a random forest method to predict patients who are at risk of developing hematoma after PCI by using parameters obtained from the patients prospectively. Result of this study, the acceptable sensitivity and specificity values obtained as 69% and 64% respectively. Hematoma risk prediction models with higher sensitivity and specificity can be obtained by using big data and important predictive parameters in similar studies in the future. By means of the rapid acquisition and processing of data of patients with portable devices, portable decision support systems can be used in every field of health. It is a nursing informatics study example using nursing data, and may be an example of the assistive decision support systems needed in the field of nursing, and it is thought to shed light on relevant studies. Through similar support decision systems that can be developed in line with the professional needs of the nursing profession, patients with risk groups can be identified in advance and the nursing process and interventions appropriate for this patient profile can be planned accordingly. Thanks to our colleagues who can combine the professional equipment of nursing with information technologies, progress can be made in areas such as data processing, storage, management, and analysis in line with the needs of the profession, and the evidence-based practices of the profession can be supported. In recent years, machine learning methods have been used based on artificial intelligence applications in the field of health. In today's academic studies in which medical informatics have come to the forefront with rapid acceleration, it is also important for the visibility of the profession to carry out informatics studies related to the nursing profession. Considering the advantages, it offers in terms of both qualities of care and time management, it is clear that there is a need for informatics themed studies in the field of nursing

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