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ORIGINAL ARTICLE / ÖZGÜN MAKALE

Artificial intelligence to predict biomarkers for new-onset atrial fibrillation after coronary artery bypass grafting

Koroner arter baypas greftleme sonrası yeni başlangıçlı atriyal fibrilasyon biyobelirteç tahmininde yapay zeka kullanımı

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ABSTRACT

Background: This study aims to identify predictors of postoperative atrial fibrillation in coronary artery bypass grafting patients using routinely collected preoperative tests.

Methods: Between January 2020 and December 2023, a total of 50 patients with postoperative atrial fibrillation (POAF group; 39 males, 11 females; mean age: 65.9±8.3 years; range, 38 to 77 years) and 50 without postoperative atrial fibrillation (non-POAF group; 41 males, 9 females; mean age: 61.8±10.0 years; range, 41 to 81 years) were randomly selected from a group of patients undergoing two or three-vessel coronary artery bypass grafting. We analyzed preoperative laboratory, demographic and intraoperative data using machine learning models.

Results: The overall incidence of postoperative atrial fibrillation was 21.69%. The three most effective biomarkers were magnesium, total iron binding capacity, and albumin, respectively. A total of 2.0 mg/dL value of magnesium was identified as a threshold value. Magnesium values below 2.0 mg/dL were considered atrial fibrillation-positive, accounting for 25% of the dataset. Total iron binding capacity values higher than 442 µg/dL were considered atrial fibrillation-positive, accounting for 12% of the dataset. The threshold value for albumin was 29 g/dL, and patients with values under this value were considered atrial fibrillation-positive, accounting for 4% of the dataset.

Conclusion: Machine learning models demonstrate encouraging results in identifying risk factors for many entities. It is of utmost importance to establish a ranking among risk factors and determine threshold values to support clinicians in decision making. This is our first experience with machine learning in this patient group after cardiac surgery. Further studies are warranted to confirm these data.

Keywords: Artificial intelligence, atrial fibrillation, coronary artery bypass grafting, machine learning, predictors.

ÖZ

Amaç: Bu çalışmada, koroner arter baypas greftleme yapılan hastalarda rutin olarak toplanan ameliyat öncesi testler kullanarak postoperatif atriyal fibrilasyonun öngördürücüleri belirlendi.

Çalışma planı: Ocak 2020 - Aralık 2023 tarihleri arasında, postoperatif atriyal fibrilasyonu olan (POAF grubu; 39 erkek, 11 kadın; yaş ortalaması: 65.9±8.3 yıl; dağılım, 38-77 yıl) ve postoperatif atriyal fibrilasyonu olmayan (non-POAF grubu; 41 erkek, 9 kadın; yaş ortalaması: 61.8±10.0 yıl; dağılım, 41-81 yıl) toplam 50 hasta, iki veya üç damar koroner arter bypass greftleme yapılan hastalar arasından rastgele seçildi. Ameliyat öncesi laboratuvar, demografik ve ameliyat sırası veriler makine öğrenimi modelleri kullanılarak analiz edildi.

Bulgular: Postoperatif atriyal fibrilasyonun genel insidansı %21.69 idi. En etkili üç biyomarker sırasıyla magnezyum, toplam demir bağlama kapasitesi ve albümin idi. Magnezyum için 2.0 mg/dL değeri bir eşik değeri olarak belirlendi. 2.0 mg/dL'nin altındaki magnezyum değerleri atriyal fibrilasyon için pozitif kabul edilerek, veri setinin %25'ini oluşturdu. Toplam demir bağlama kapasitesi 442 µg/dL'nin üzerindeki değerler atriyal fibrilasyon için pozitif kabul edilerek, veri setinin %12'sini oluşturdu. Albümin için eşik değeri 29 g/dL idi ve bu değerin altındaki albümin düzeyleri atriyal fibrilasyon için pozitif kabul edilerek, veri setinin %4'ünü oluşturdu.

Sonuç: Makine öğrenimi modelleri, birçok hastalık için risk faktörlerini belirlemede teşvik edici sonuçlar göstermektedir. Risk faktörleri arasında sıralama yapmak ve eşik değerlerini belirlemek, klinik karar destek sistemlerini güçlendirmek adına son derece önemlidir. Bu, kalp cerrahi sonrası bu hasta grubunda makine öğrenimini kullanmadaki ilk deneyimimizdir. Bu verileri doğrulamak için daha fazla çalışmaya ihtiyaç vardır.

Anahtar sözcükler: Yapay zeka, atriyal fibrilasyon, koroner arter baypas greftleme, makine öğrenimi, öngördürücü.

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Postoperative atrial fibrillation (POAF) is a common complication after coronary artery bypass grafting (CABG). Its incidence varies in the literature up to 40% of patients after isolated CABG.[1] Postoperative atrial fibrillation increases the risk of cerebrovascular events, congestive heart failure, myocardial infarction, postoperative mortality, and prolonged hospital stays. Re-entry and triggering activity, including perioperative inflammation, oxidative stress, pain, electrical remodeling, electrolyte disturbance and ischemia are two known probable mechanisms of atrial fibrillation (AF).[2] Therefore, it is of utmost importance to identify the risk of POAF before surgery.

To date, several studies have been performed to predict POAF. Heat shock proteins were shown as markers for AF development.[3,4] Electrolyte disturbances,[5] vitamin deficiencies,[6] metabolic states,[7] demographic features,[8] genetic factors[9] and many others have also been evaluated to predict POAF. However, some markers and predictors are not cost-effective and sometimes commercially unavailable. Another question is the importance-ranking of these markers and predictors.

In the present study, we aimed to identify predictors of new-onset POAF using a pool of routinely performed preoperative tests at our institution using machine learning (ML) methods.

PATIENTS AND METHODS

This retrospective study was conducted at Antalya Training and Research Hospital, Department of Cardiovascular Surgery between January 2020 and December 2023. A total of 50 patients with POAF (POAF group; 39 males, 11 females; mean age: 65.9±8.3 years; range, 38 to 77 years) and 50 without POAF (non-POAF group; 41 males, 9 females; mean age: 61.8±10.0 years; range, 41 to 81 years) were randomly selected from a group of 265 patients undergoing two or three-vessel CABG performed by two experienced cardiovascular surgeons. The only inclusion criterion was having isolated CABG for two or three-vessel disease. All patients were operated under cardiopulmonary bypass. Patients with AF prior to surgery and patients with postoperative complications causing re-intervention, prolonged intensive care unit stay (ICU), delayed extubation, and previous renal failure (glomerular filtration rate <60 mL/min/1.73 m^2) were excluded from the study. A written informed consent was obtained from each participant. The study was approved by the Antalya Education and Research Hospital Clinical Research Ethics Committee (date: 04.05.2023, no: 6/6). The study was conducted in accordance with the principles of the Declaration of Helsinki.

CABG procedure

Routine cardiac medications were continued until day of surgery, except for clopidogrel, which was stopped at least five days before surgery. Beta-blocking agents were routinely prescribed until the day of surgery. Before anesthetic induction complete hemodynamic monitoring was performed in the operating room. On-pump surgery was performed with mild hypothermia with the use of aortic cross-clamping and antegrade cold blood cardioplegia. Patients were heparinized at 300 IU/kg to achieve an activated clotting time of >400 sec. Heparin was neutralized with 1 mg protamine sulfate per 100 IU given.

Diagnosis of new-onset atrial fibrillation

Diagnosis of AF was made according to the 2010 guidelines of the European Society of Cardiology (ESC), based on abnormalities on electrocardiogram (ECG), which lasted at least 30 sec and was characterized by sustained arrhythmia, irregular RR intervals, absent P waves and different intervals between atrial contractions (cycle <200 ms). All patients were routinely monitored in the ICU for two days after cardiac surgery and, then, transferred to the ward where an ECG was done once daily and heart rate and blood pressure were measured every 4 h. In case of any disturbance of heart rate, an actual ECG was done. A new-onset of POAF was defined as an AF from time after cardiac surgery until discharge on postoperative Day 5.

Sixteen patients were excluded from the study. Finally, a total of 54 (21.69%) of the patients developed POAF.

Data collection

All routine laboratory results obtained at least 48 h before surgery were collected. Demographic, echocardiographic, and perioperative data were also recorded.

Analysis using machine learning

Several classification models were used for data comparison. Description of the models are provided below.

Decision Tree (DT) is a classification algorithm good at handling erroneous data. The main aim of this algorithm is to minimize the error and determine the appropriate tree model.

Naive Bayes (NB) formula represents the likelihood of a class given a set of independent features. In simple terms, it calculates the probability of a patient developing POAF based on the observed features:

$$\text{Eq.1: } P(Y=y\_i|X=x_k)=\frac{P(X=x_k|Y=y_i)P(Y=y_i)}{\sum_j P(X=x_k|Y=y_i)P(Y=y_i)}$$

In Eq.1, Y is the Boolean value, X is the Boolean vector, and i indicates the class. By estimating the kth value in X, the ratio between the target class value and the total target value should be found.

Probabilistic Data Association (PDA) is a classification algorithm that can estimate values in real-time. This algorithm approach is similar to Bayesian. Firstly, an area is chosen in the problem and the value is searched in this area. The area is updated until the value is detected. The value detections are independent. The formulation is as follows:

$$\text{Eq.2: } P\{\epsilon_1(k)|Z^k\} = P\{\epsilon_1(k)|Z^k), m(k), Z^{k-1}\}$$

In Eq. 2, ε is the value that depends on the originated targets, Z(k) is the very last data, and Z^{k-1} and Z^k are the broken data parts. The Bayesian approach can also be used in this formulation.

Random Ferns (RFerns) is a classification algorithm that applies the identical series to all inputs. This algorithm uses multiplication rather than addition to compute. The RFerns algorithm uses an improved NB algorithm by partitioning the trees into ferns to consider the correlation between features. The formulation is as follows:

$$\text{Eq.3: } P\{f_1, f_2 ...|C=c_i) = \prod_{k=1}^{M} P(F_k|C=c_i)$$

In Eq. 3, while M represents the groups of features, c represents class, and C is a random class. In addition, f is the binary features set, and P is the uniform prior.

K Nearest Neighbour (KNN) is an effective classification algorithm that places the value into the appropriate class. For this, the algorithm calculates the distance between variables. The target value is, then, placed into the nearest class.

$$\text{Eq.4: } M(w, W_i) = \sqrt{\sum_{j=1}^{d}(w_j - W_{ij})^2}$$

In Eq. 4, w is the space vector, W is the class known tuple, d is distance, i and j are the class indicators. The smallest result of the formula gives the class of the unknown classed value.

Statistical analysis

Statistical analysis was performed using the IBM SPSS version 20.0 software (IBM Corp., Armonk, NY, USA). Continuous variables were presented in mean ± standard deviation (SD) or median (min-max), while categorical variables were presented in number and frequency. The Mann-Whitney U test was performed to analyze continuous variables, while the chi-square test was applied for categorical variables. Significant predictors of POAF were identified using the receiver operating characteristic (ROC) curve. A *p* value of <0.05 was considered statistically significant.

Table 1. Demographic and baseline data

	POAF group		non-POAF group		
	n	Mean±SD	n	Mean±SD	*p*
Age (year)		65.9±8.3		61.8±10.0	<0.05
Sex					
Male	39		41		>0.05
Height (cm)		164.84±6.973		168.78±8.214	<0.05
Weight (kg)		79.86±18.617		76.44±12.319	>0.05
Body mass index (kg/m²)		29.41±6.921		26.75±3.45	<0.05
Body surface area (m²)		1.89±0.246		1.88±0.186	>0.05
Smoking habit	40		41		>0.05
Chronic obstructive pulmonary disease	13		7		>0.05
Diabetes mellitus	26		24		>0.05

POAF: Postoperative atrial fibrillation; SD: Standard deviation.

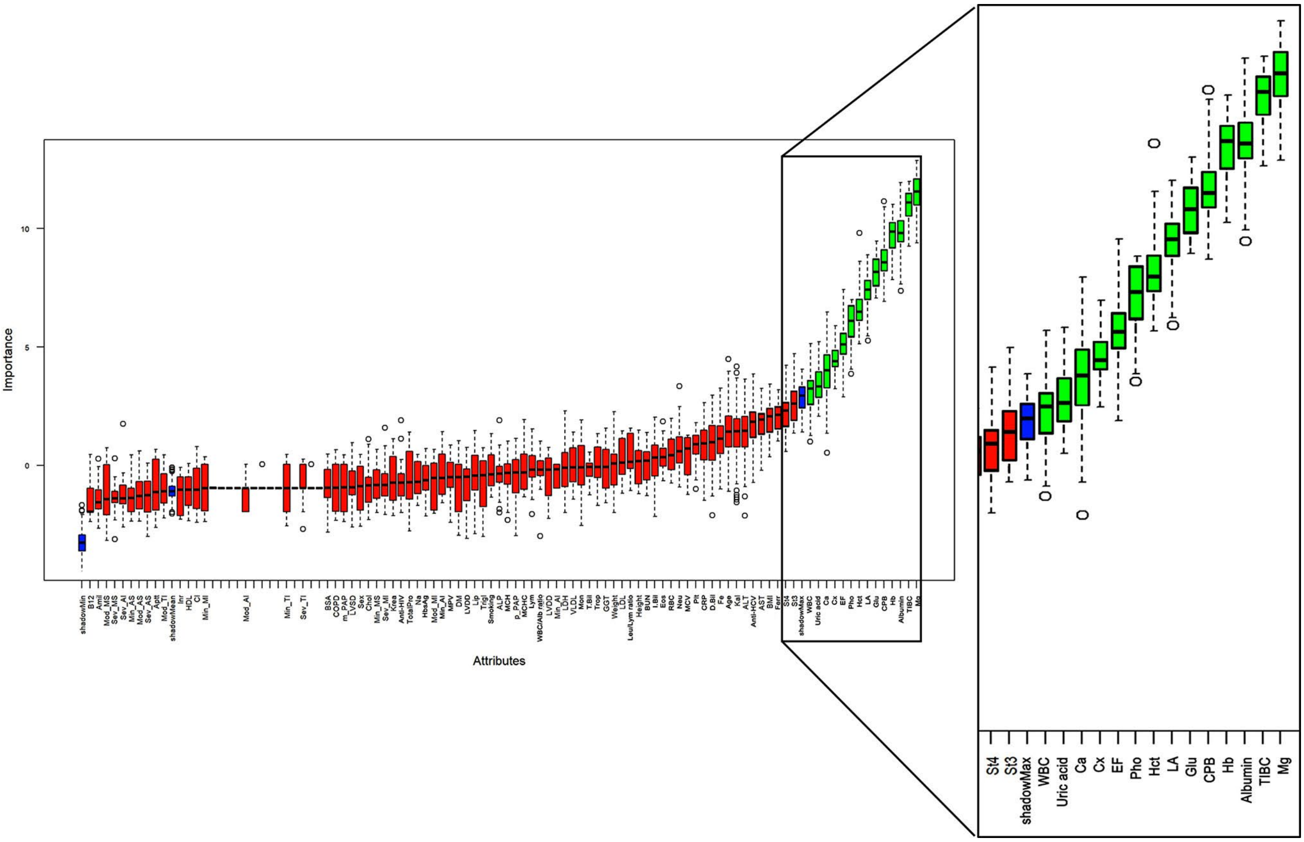

Figure 1. Boruta feature selection algorithm.

ALP: Alkalen phosphatase; ALT: Alanin animotransferase; APTT: Activated partial thromboplastin time; AST: Aspartat amino transferase; BMI: Body mass index; BSA: Body surface area; BUN: Blood urea nitrogene; Ca: Calcium; Cl: Chlorine; COPD: Chronic obstructive pulmonary disease; CRP: C-reactive protein; Cx: Cross clamp time; D.Bil: Direct bilirubin; DM: Diabetes mellitus; EF: Ejection fraction; Eos: Eosinophyl ; Fe: Iron; Ferr: Ferritin; GGT: Gama glutamil transferaz; Glu: Glucose; Hb: Hemoglobin; HbsAg: HbS antigen; Hct: Haematocrit; HCV: Hepatit C virus; HDL: High density lipoprotein; HIV: Human immun deficiency virus; I.Bil: Indirect bilirubin; INR: International normalized ratio; Kal: Kalium; Krea: Creatinin; LA: Left atrium diameter; LDH: Lactate dehydrogenase; LDL: Low debsity lipoprotein; Leu: Leucocyte count; Lip: Lipase; LVDD: Left ventricle diastolic diameter; Lym: Lymphocyte count; MCH: Mean corpuscular hemoglobin; MCHC: Mean corpuscular hemoglobin concentration; MCV: Mean corpuscular volume; Mg: Magnesium; MinAI: Minimal aortic insufficiency; MinAS: Minimal aortic stenosis; MinMI: Minimal mitral insufficiency; MinMS: Minimal mitral stenosis; MinTI: Minimal tricuspit insufficiency; ModMS: Moderate mitral stenosis; ModAI: Moderate aortic insufficiency; ModAS: Moderate aortic stenosis; ModMI: Moderate mitral insufficiency; ModTI: Moderate tricuspid insufficiency; Mon: Monocyte count; mPAP: Mean pulmonary artery pressure; MPV: Mean platelet volume; Neu: Neutophil count; Pho: Phosphor; Plt: Platelet count; pPAP: Pea pulmonary artery pressure; RBC: Red blood cell count; SevAI. Severe aortic insufficiency; SevAS: Severe aortic stenosis; SevMI: Severe mitral insufficiency; SevMS: Severe mitral stenosis; SevTI: Severe tricuspid insufficiency; ST3: Free T3; ST4: Free T4; T.Bil: Total bilirubin; TIBC: Total iron binding capacity; Trigl: Triglyceride; Trop: Troponin; TT: Thromboplastin time; VLDL: Very low density lipoproetin; WBC: Wight blood cell.

RESULTS

Demographic and baseline data of both groups are shown in Table 1.

Using the ML systems, there were 91 independent and one dependent variables for a total of 100 patients. The dataset consisted of a matrix consisting of 100 rows and 92 columns.

The Boruta Feature Selection Algorithm (BFSA) was used to determine the importance of independent features. Figure 1 illustrates the distribution of important features selected through the BFSA. The red colored features of the BFSA appear as features without effect on the classification problem and could be discarded. The green colored features were identified to be important for the classification problem. The importance ranking among these features increases toward the right on the horizontal axis. These features were continued in the creation of ML models. The data distribution and numerical values of highly ranked variables in the dataset are shown in the histogram chart in Figure 2 and Table 2, respectively.

The graph obtained using the DT model is seen in Figure 3. This chart shows how classification is performed by representing two classes according to certain threshold values of three separate features.

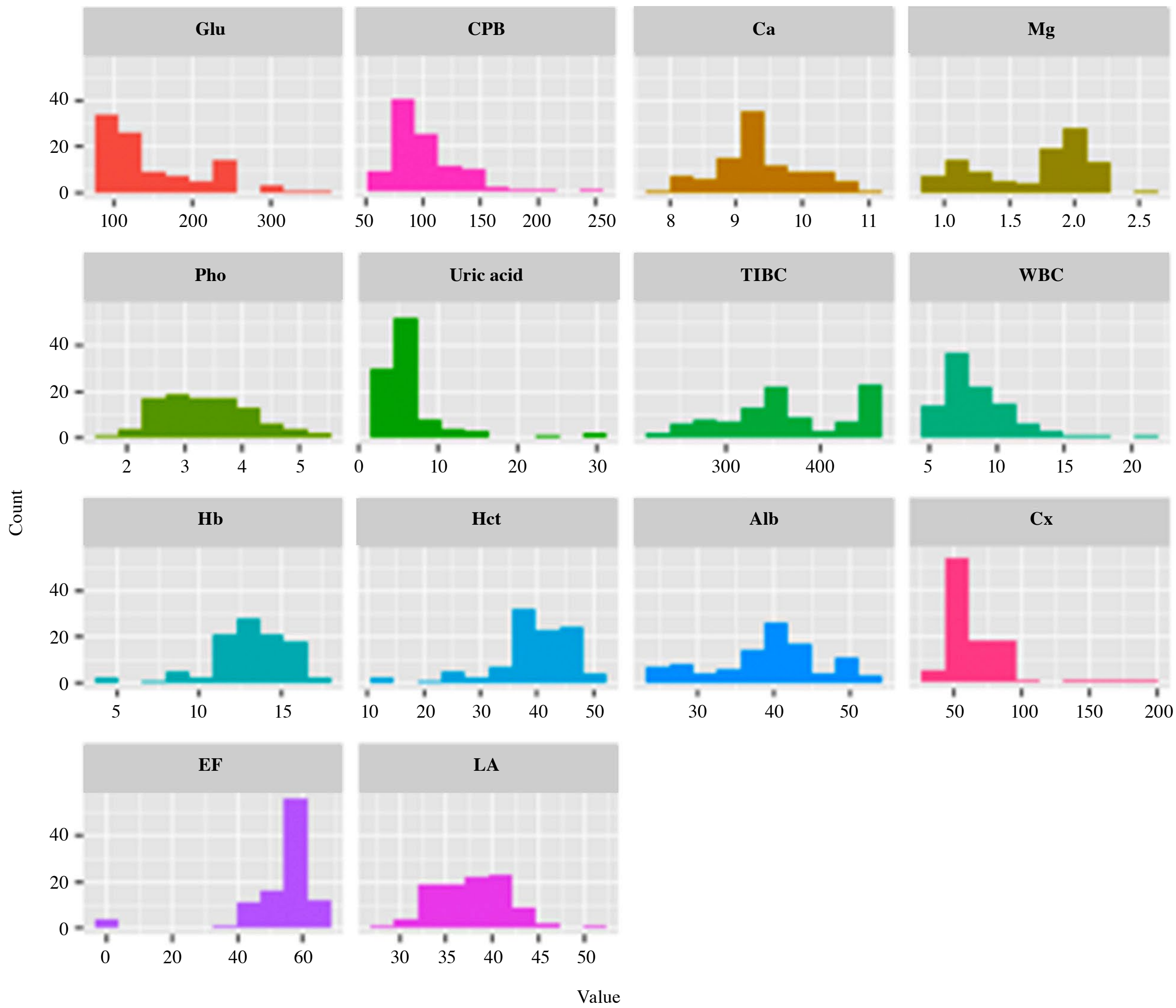

Figure 2. Histogram chart of highly ranked parameters.

Glu: Glucose; CPB: Cardiopulmonary bypass time; Mg: Magnesium; Pho: Phosphate; TIBC: Total iron binding capacity; WBC: Wight blood cell count; Hb: Hemoglobin; Hct: Hematocrit; Alb: Albumin; Cx: Cross clamp; EF: Ejection fraction; LA: Left atrium diameter.

The three most important features in predicting POAF are magnesium, TIBC and albumin, respectively. The mean magnesium level was 1.83±0.391 mg/dL in POAF group and 2.04±0.122 mg/dL in non-POAF group. Normal ranges for magnesium at our institution's laboratory are 1.8 to 2.6 mg/dL. The 2.0 mg/dL value of magnesium was determined by the DT algorithm as the threshold value. Patients with magnesium values below the threshold value were AF-positive and constituted 25% of the dataset. The second most ranked parameter was TIBC, and the mean values in POAF and non-POAF groups were 385.26±9.046 µg/dL and 341.18±61.585 µg/dL, respectively. Regarding to our laboratory references both levels were within the normal ranges, but the difference was significant. A TIBC value of 442 µg/dL is the threshold value. Patients with TIBC values greater than this value were AF-positive and constituted approximately 12% of the dataset. Although in normal ranges albumin level was significantly lower in the POAF group (35.61±6.555 g/dL *vs*. 42.47±6.138 g/dL). The albumin threshold value was determined as 29 g/dL. Patients with values below this threshold value were AF-positive and constituted 4% of the entire dataset.

Eighty percent of the total observation amount was allocated for training each ML model.

Table 2. Results of high ranked parameters

	POAF group	non-POAF group		
	Mean±SD	Mean±SD	Normal ranges	***p***
Magnesium (mg/dL)	1.83±0.391	2.04±0.122	1.9-2.5	<0.001
Total iron binding capacity (µg/dL)	385.26±59.046	341.18±61.585	225-480	<0.001
Albumin (g/dL)	35.61±6.555	42.47±6.138	35-52	<0.001
Hemoglobin (g/dL)	12.35±2.789	13.96±1.662	12.5-16.0	<0.001
Cardiopulmonary bypass time (min)	54.90±11.021	54.18±16.105		<0.05
Glucose (mg/dL)	166.14±68.246	128.04±51.844	74-106	<0.05
Left atrium diameter (mm)	38.96±3.063	36.98±4.744	22-45	<0.05
Hematocrit (%)	37.34±8.007	41.67±4.802	37-47	<0.05
Phosphor (mg/dL)	3.63±0.875	3.04±0.643	2.5-4.5	<0.001
Ejection fraction (%)	51.92±16.251	55.60±8.429	>53	>0.05
Cross-clamp time (min)	34.62±9.828	33.98±14.710		>0.05
Calcium (mg/dL)	9.32±0.567	9.39±0.692	8.8-10.6	>0.05
Uric acid (mg/dL)	7.53±6.121	5.32±1.281	2.6-7.2	<0.05
White blood cell count	8.40±3.322	8.79±2.162	4-10.5	>0.05

POAF: Postoperative atrial fibrillation; SD: Standard deviation.

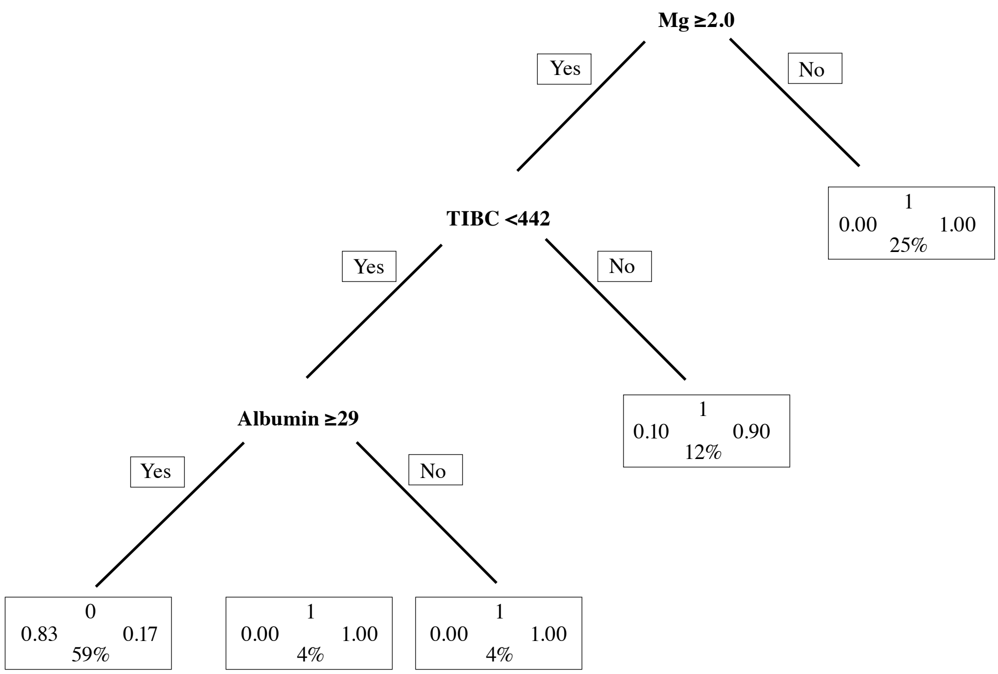

Figure 3. Decision tree of most important properties.

Mg: Magnesium; TIBC: Total iron binding capacity.

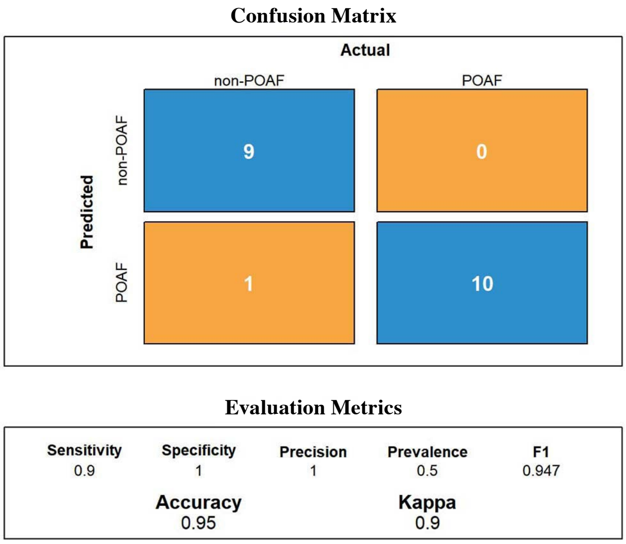

Figure 4. Accuracy of DT model.

POAF: Postoperative atrial fibrillation; DT: Decision tree.

The remaining 20% was reserved for testing the trained models. By applying 10-fold cross validation to the dataset allocated for training, an attempt was made to prevent possible memorization in the training of the models. The resulting five separate ML models were examined by considering the accuracy and kappa evaluation metrics. In addition, the results were obtained by resampling 50 times for a 95% confidence interval (CI).

The test results of the DT model were obtained from 20 observations. Nine out of 10 patients who had no AF were correctly classified as non-POAF. However, the model made an error by classifying one patient who was non-POAF as POAF. On the other hand, all patients who had POAF were predicted to have POAF and were classified correctly. Accordingly, accuracy: 0.95, kappa: 0.9, sensitivity: 0.9, specificity: 1, precision: 1, prevalence: 0.5 and F1 score value was obtained as 0.947 (Figure 4). Comparison of ML models is demonstrated in Table 3. The ROC analysis of ML models is depicted in Figure 5.

DISCUSSION

Atrial fibrillation is a critical complication after cardiac surgery. In this study, we evaluated isolated CABG patients. Identifying patients with an increased risk of developing POAF is more likely to benefit from preventive therapy. Therefore, risk prediction can be a fundamental strategy to prevent AF. Also, guidelines recommend different strategies to prevent AF. On the other hand, prevention of AF increases long-term survival. Sihombing et al.[10] reported that POAF patients had a mortality rate of 15.52% *vs*. 3.62% in non-POAF patients. Similarly, Malhotra et al.[11] found a 16.6% mortality rate in POAF group *vs*. 2.9% in non-POAF group.

In the present study, we focused on defining features and establishing classification models in AF. As a result of the analyses, 14 features that were likely to affect the classification process of patients according to whether they develop AF or not were identified. Magnesium, TIBC, and albumin were determined to be the three most effective properties, respectively.

Magnesium, which is an essential cofactor for the sodium-potassium adenosine triphosphate pump, has effects on the cardiac conduction system. Disruption or alteration of this pump in the setting of hypomagnesemia may impact myocardial excitability. Magnesium infusion prolongs atrioventricular conduction, while low magnesium levels increase sinus node automaticity.[12] Hypomagnesemia

Table 3. Comparison of machine learning models

	DT	NB	RFerns	PDA	KNN
Sensitivity	0.9	0.9	0.8	0.9	0.8
Specifity	1	0.9	0.9	0.7	0.5
Precision	1	0.9	0.889	0.75	0.615
Prevalence	0.5	0.5	0.5	0.5	0.5
F1 score	0.947	0.9	0.842	0.818	0.696
Accuracy	0.95	0.9	0.85	0.8	0.65
Kappa	0.9	0.8	0.7	0.6	0.3

DT: Decision tree; NB: Naive Bayes; RFerns: Random Ferns; PDA: Probabilistic Data Association; KNK: K Nearest Neighbour.

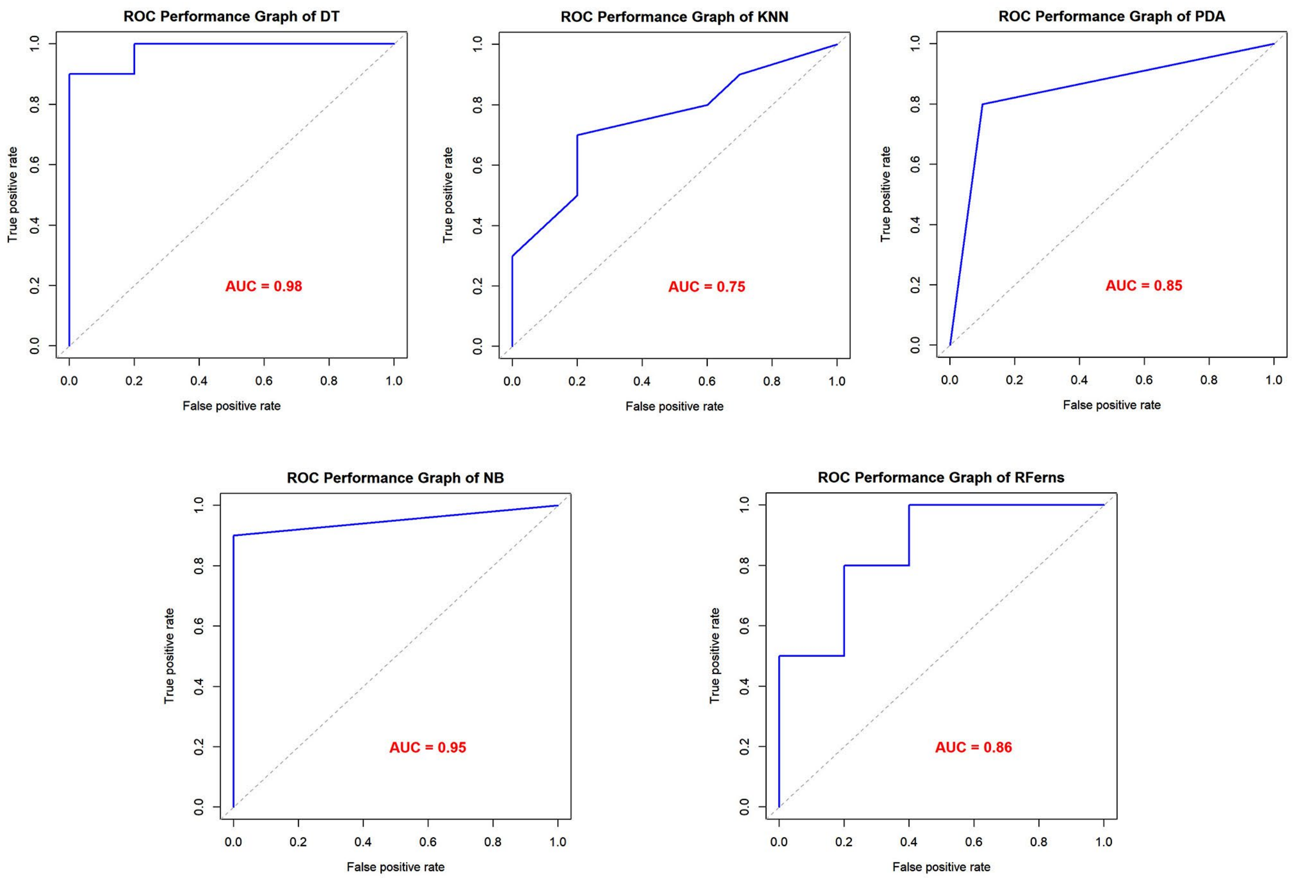

Figure 5. ROC analysis of ML models.

ROC: Receiver operating characteristic; DT: Decision tree; KNN: K Nearest Neighbour; PDA: Probabilistic Data Association; NB: Naive bayes; RF: Random ferns; ML: Machine learning; AUC: Area under the curve.

is a common finding in pre- and postoperative situations, and this contributes to AF onset.[13] A study conducted by Burrage et al.[14] showed that low serum magnesium levels were associated with AF after cardiac surgery. Most of the studies in the literature demonstrate beneficial effects of magnesium therapy except for one conducted by Lancaster et al.[15] postulating that supplementation of magnesium did not protect against AF. On the other hand, a meta-analysis published by Gu et al.[16] found that intravenous magnesium prevented AF after CABG. The supplementation of magnesium to cardioplegia is also effective in preventing AF.[17] Additionally, in off-pump CABG, administration of magnesium pre- and postoperatively was beneficial in preventing AF.[14] In their systematic review, Turagam et al.[18] compared the effects of preoperative regimens of magnesium to intra- and postoperative administrations. Preoperative magnesium was more effective in preventing AF than intra- and postoperative administration. A debating factor is the dose and duration of treatment to reach adequate levels of intracellular magnesium;[19] therefore, studies for determining the optimal dosing and timing for magnesium therapy seem to be essential.

In our study, TIBC as an effective property was an interesting finding. To the best of our knowledge, there are no studies in the literature demonstrating a direct correlation between TIBC and AF. Rather, TIBC may be an indirect indicator for serum iron. Only a few studies have investigated the correlation between iron and AF. In a review by Hanna-Rivero et al.,[20] the relationship between iron status and AF was clearly documented and Keskin et al.[21] showed that iron deficiency was common among AF patients. Although not widely discussed in the literature, levels of causality are also critical. In our study, the mean ferritin level was 123.03±78.625 in POAF group and 124.39±79.560 in non-POAF group. The fact that the TIBC value increased in the POAF group, but the ferritin value was normal may raise the question of whether there may be a relationship between inflammation and POAF rather than iron deficiency or anemia. However, regarding to this study, TIBC still seems to be a novel marker. Further studies are needed to fully elucidate the biochemical causality relationship with AF. Hanna-Rivero et al.[20] also suggested that inflammation had a significant role in the pathogenesis of AF, which may explain normal ranges of ferritin despite high -TIBC levels.

Albumin is another effective biomarker. Although the causality could not be established, low levels of albumin are directly associated with AF development.[22] The importance of albumin was also demonstrated in a study by Schamroth Pravda et al.[23] where low albumin levels predicted AF recurrence after ablative therapies.

Currently, ML models are effective tools for predicting operative outcomes after CABG. This may benefit quality assessment and clinical decision making. The interpretation of ECG parameters using ML models has been shown to be effective in predicting AF.[24] Furthermore, ML models appear to be superior to clinical scoring tools in predicting AF, as well as mortality.[25] El-Sherbini et al.[26] published a review postulating that ML models may offer an advantage over conventional risk scores due to their ability to analyze different correlations and their potential for incorporating several demographic and clinical variables in predicting AF after cardiac surgery.

Of note, this study is our first attempt using ML models to predict AF after CABG. We believe that it was important to determine a ranking in probably effective biomarkers. Another important finding was the threshold values of the three most important biomarkers; i.e., magnesium, TIBC, and albumin. Although favorable results can be obtained with ML in small sample sizes, it would be more accurate to work with larger case series for an ambitious result. Indeed, including features such as preoperative renal failure and prolonged ICU stay in large case series would be beneficial in terms of diversity.[27] On the other hand, a remarkable feature of our study was that we analyzed all routine preoperative laboratory parameters, demographic data and intraoperative data. It would be more possible to make a generalization with studies conducted with increased number of cases. The ML studies should be conducted with larger case series. However, the accuracy of the threshold values also needs to be tested. The impact of preoperative magnesium, TIBC, and albumin optimization on long-term outcomes should be investigated in further studies.

In conclusion, many parameters in the literature demonstrate a correlation with atrial fibrillation and even with postoperative atrial fibrillation. Taken together, the ranking of the parameters or properties are still missing. Machine learning is useful for establishing the ranking among these parameters or properties. Our study findings suggest that preoperative levels of magnesium, albumin, and total iron binding capacity may help to predict postoperative atrial fibrillation risk. However, it should be kept in mind that this study was conducted on a limited scale due to the low rate of atrial fibrillation in a selected population. Therefore, the findings of the study need to be strengthened by external validation for their applicability. Future studies should involve larger patient populations to validate these predictors and refine machine learning models.

Data Sharing Statement: The data that support the findings of this study are available from the corresponding author upon reasonable request.

Author Contributions: Idea: B.A.; Design: B.A., O.O., M.Ç.; Supervision: M.Y., G.A.; Data collection. M.G.S.; Literature revirew: B.A., M.G.S., G.A.; Crtical review: M.Y., O.O.

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