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Diagnosis of Acute Coronary Syndrome with a Support Vector Machine

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Abstract Acute coronary syndrome (ACS) is a serious condition arising from an imbalance of supply and demand to meet myocardium's metabolic needs. Patients typically present with retrosternal chest pain radiating to neck and left arm. Electrocardiography (ECG) and laboratory tests are used indiagnosis. However in emergency departments, there are some difficulties for physicians to decide whether hospitalizing, following up or discharging the patient. The aim of the study is to diagnose ACS and helping the physician with his decisionto discharge or to hospitalizevia machine learning techniques such as support vector machine (SVM) by using patient data including age, sex, risk factors, and cardiac enzymes (CK-MB, Troponin I) of patients presenting to emergency department with chest pain. Clinical, laboratory, and imaging data of 228 patients presenting to emergency department with chest pain were reviewedand the performance of support vector machine. Four different methods (Support vector machine (SVM), Artificial neural network (ANN), Naïve Bayes and Logistic Regression) were tested and the results of SVM which has the highest accuracy is reported. Among 228 patients aged 19 to 91 years who were included in the study, 99 (43.4 %) were qualified as ACS, while 129 (56.5 %) had no ACS. The classification model using SVM attained a 99.13 % classification success. The present study showed a 99.13 % classification success for ACS diagnosis attained by Support Vector Machine. This study showed that machine learning techniques may help emergency department staff make decisions by rapidly producing relevant data.

Keywords Acute coronary syndrome · Artificial intelligence · Support vector machine · Machine learning

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Introduction

Coronary artery diseases (CAD) are the most common and serious conditionsleading to death. They are responsible for deaths with a rate of 46 % in Europe [1]. Acute coronary syndrome (ACS) represents one of the major public health issues owing to its high rates of morbidity, mortality as well as higher costs associated with its treatment and rehabilitation [2]. In the United States, it is stated that 1.500.000 people are hospitalized with ACS each year and 229.6 per 100000 rate of death [3, 4].

ACS is classified as non-ST elevation myocardial infarction (NSTEMI) and ST elevation myocardial infarction (STEMI). Unstable angina pectoris (UAP) is another definition of myocardial ischemia with the symptoms onset at rest and independent of electrocardiographic findings [3 days]. Although UAP is not an infarction, it is classified as NSTEMI in new guidelines [4, 5]. Myocardial infarction typically occurs as a result of atherosclerosis or sudden formation of a fibrin plug. Systolic and diastolic functions are impaired in ischemic myocardium, causing reduced cardiac output and cardiac failure or shock. Apart from myocardial injury, fatal

arrhythmias may ensue as a result of ischemia or infarction of components of cardiac conduction system as a result of blockage of arteries supplying these structures. Restoration of myocardial blood supply may either be achieved by collateral vessel formation or lysis of the formed fibrin plug. The amount of salvaged myocardial tissue is dependent on the timing (early vs. late) restoration of myocardial blood supply.

ACS may present with chest pain, difficulty breathing, cardiac asystole, syncope, or shock. Of these, chest pain is the most common presenting symptom. Patients typically admit to healthcare institutions with retrosternal chest pain radiating to neck or left arm. Atypical chest pain located to right arm, right shoulder, back, or epigastrium. Accompanying symptoms such as dyspnea, dizziness, syncope, presyncope, nausea, vomiting, fatigue, or sweatingmay also be present. Pain may be absent in elderly patients and in diabetics. Physical examination findings are variable and not specific to myocardial infarction [5, 6].

History has an important role in differential diagnosis of ACS in patients presenting to emergency department with chest pain. Risk factors for ACS include hypertension, diabetes mellitus, dyslipidemia, smoking, and family history of coronary artery disease.

On electrocardiogram (ECG), ACS patientscan have hyperacuteT waves, negative T waves, ST segment elevation, pathological Q waves, or ST changes not specific to myocardial infarction. However normal ECGs can also be encountered in some patients of ACS. Therefore, a normal ECG cannot rule out ACS diagnosis, but rather serial ECGs or comparison of ECG changes with prior ECG changes may aid in diagnosis. The most commonly used laboratory tests for diagnosis of ACS are creatine kinase (CK), creatine kinase-MB (CK-MB), myoglobin, troponin T (cTnT), and troponin I (cTnI). Although CK-MB and myglobin levels are early elevated in myocardial injury, Troponin I is found more sensitive than the other molecules [7].

Echocardiography is an imaging tool to show wall motion abnormalities of ACS, ejection fraction and other differential diagnosis of chest pain (aortic dissection, pericardial tamponade etc.).

In the literature, there are risk scores defined to determine the mortality and survival risks of the patients suspected with ACS according to patients undependable and dependable variables (Table 1). TIMI (Thrombolysis In Myocardial Infarction) GRACE (Global Registry of AcuteCoronaryEvents) EMMACE (Evaluation of Methods of Management of AcuteCoronaryEvents) PURSUIT (PlateletglycoproteinIIb/IIIa in Unstableagina: ReceptorSuppression Using Integrilin) and GUSTO (Global Utilization of Streptokinase and Tissue Plasminogen Activator for Occluded Coronary Arteries) are the risk scores of ACS. The risk scores helps the diagnose, treatment and mortality prediction [3].

Age is the independible variable of all scores. Gender is a variable used in PURSUIT. Heart rate and SBP is used in GRACE, EMMACE, PURSUIT and GUSTO (heart rate only).

History of ACS and risk factors as smoking, hyperlipidemia, family history, ASA use are the mortality factors.

ST changes is a diagnostic factor of ACS and also used in risk scores. ST elevation is a type of ACS as “ST elevated MI”. Ejection Fraction is a marker of heart failure. The patients could have a heart failure history before or the heart failure could occur instantly due to ACS.

Cardiac markers are specific markers of heart. Their elevation during chest pain are significant of ACS.

Higher scores are related with high mortality rates which requires hospitalization and follow up.

An artificial intelligence example, machine learning technique learn from previous datasets and make decisions to future sample. Some machine learning techniques are Naïve Bayes, Classification Tree, Support Vector Machine, K Nearest Neighbour, Artificial Neural

Table 1 Risk Scores of Acute Coronary Syndromes (TIMI: Thrombolysis In Myocardial Infarction GRACE: Global Registry of Acute Coronary Events EMMACE: Evaluation of Methods of Management of Acute Coronary Events PURSUIT:, Platelet glycoproteinIIb/IIIa in Unstable angina: Receptor Suppression Using Integrilin GUSTO: Global Utilization of Streptokinase and Tissue Plasminogen Activator for Occluded Coronary Arteries HR: Heart rate SBP: Systolic blood pressure EF:ejection fraction CAD:coronary artery disease ASA:asetylsalisilic acid)

	Age	Gender	HR	SBP	ST Changes	Heart failure signs	Risk factors	Angina	EF	History of CAD	ASA use	Cardiac marker	Creatinin
TIMI	+				+		+	+		+	+	+	
GRACE	+		+	+	+	+						+	+
EMMACE	+		+	+									
PURCUIT	+	+	+	+	+	+		+					
GUSTO	+		+			+			+	+			

Network. Besides risk scores; machine learning techniques have been successfully used in diagnose in medicine. Computer assisted decision making for myocardial infarction and cancer prediction have been studied for more than two decades [8–10].

Techniques for decision to follow up or discharge in suspected ACSpatientsshould include the most appropriate combinations of clinical, ECG, laboratory, and imaging techniques and aim at determining the most logical and cost effective one of these combinations. However the less expensive techniques as history and physical examination can lead overdiagnose or misdiagnose of ACS which cause patient loss or unnecessary cost increases. With this purpose, diagnostic methods with high accuracy can improve health and lower costs.

In our study, we use support vector machine and machine learning techniques to make decision of hospitalization or discharge of patients admitting emergency department with chest pain.

Materials and methods

Patient selection and collection of patient data

This study included 228 patients who presented to emergency department with typical chest pain and were consulted with cardiology department for suspected acute coronary syndrome between January 2013 and April 2013. This study was approved by Mersin University Research and Training Hospital Ethics Committee. Ninety-nine patients had been hospitalized with the diagnosis of acute coronary syndrome according to risk scores and positive EKG or echocardiography findings and 129 patients did not. The patients who refused diagnostic and therapeutic interventions, and those who had chest pain not suggestive of acute coronary syndrome were excluded. Sex, age, past history, ECG, CK-MB and troponin-I level, and echocardiographic data of the patients were studied. ST elevation and new occurring left bundle branch blockage (LBBB) is a certain finding of ACS, other ECG findings like ST depression, T inversion, subacute T waves are high risk of ECG. Echocardiographic study was carried out with Philips HD11XE device (Philips, Holland) to study ventricular function and ejection fraction. Ejection fraction was recorded as low when it was below 50 %. Hypokinesia and akinesia leads to ACS while other findings rule out differential diagnosis of heart and lung. A past history was considered positive when it included smoking, family history, diabetes, hypertension, hyperlipidemia, and any previous cardiac ischemia. Admission levels of CK-MB and Troponin I were also included in the analysis. The reference values for CK-MB and Troponin I were set to 0–5 and 0.04 ng/ml, respectively. Similarly, admission for ECG and echocardiography were also recorded. The patients were hospitalized by the cardiology department to coronary care unit were considered to have “acute coronary syndrome” due to risk scores of ACS. ACS data parameters were given on Table 2.

Gender of the patients are recorded as male or female. History of smoking, family history, diabetes, hypertension, hyperlipidemia, previous heart attack is categorized as yes /no. Present of one is accepted as yes. ECG findings are categorized into 23 groups as Normal sinus rhythm, right bundle branch blockage, left bundle branch blockage, ST elevation, ST depression, Atrial fibrillation, Pathologic Q, bradyarythmia, left ventricular hypertrophy, pace ryhtm,

Table 2 ACS dataset parameters

	Definition	Value
Gender	Gender of Patient	Categoric (M, F)
Age	Age of patient	Continuous (19–91)
History (Any of one’s presence is “yes”; None of them is stated as “no”	History of smoking, family history, diabetes, hypertension, hyperlipidemia, previous cardiac ischemia	Categoric (Y, N)
ECG	Electrocardiography findings (Normal sinus rhythm, right bundle branch blockage, left bundle branch blockage, ST elevation, ST depression, Atrial fibrillation, Pathologic Q, bradyarythmia, left ventricular hypertrophy, pace ryhtm, other ischemic changes, T negativity, wolf parkinson white, supraventriculartachicardia, and other combinations)	Categoric (1–23)
CK-MB (0–5 ng/ml)	CK-MB values	Continuous (0,01–300)
Troponin I (<0,5 ng/ml)	Troponin I values	Continuous (0–50)
Echocardiography	Echocardiography findings (Normal echocardiography, low EF, hypokinesia, dilated cardiomyopathy, ivs perforations, high pulmonary artery pressure, and other combinations)	Categoric (1–11)

Table 3 ACS data: Age, CK-MB (0–5 ng/ml) and Troponin I (<0.5 ng/ml) distribution (Mean-SD)

	High suspicion of ACS 99	Lowsuspicion of ACS 129	*p*-values
Age	61.5 (13.89)	57.5 (14.03)	0.115
ck-mb (0–5 ng/ml)	3.7 (62.48)	1.255 (2.83)	0.002
Troponin I (<0.5 ng/ml)	1.55 (514.30)	0.028 (0.39)	0.234

other ischemic changes, T negativity, wolf parkinson white, supraventriculartachicardia, and other combinations. They are recorded as numbers. Cardiak markers CK-MB and troponin values are recorded. Table 3 shows mean and standard deviation values for age, CK-MB (0–5 ng/ml), and Troponin I (<0.5 ng/ml). Echocardiographic findings are categorized into 11 groups as Normal echocardiography, low EF, hypokinesia, dilated cardiomyopathy, ivs perforations, high pulmonary artery pressure, and other combinations. P values are not found significant with outcome. This is due to the other reasons of troponin and ckmb positivity. Troponin can increase in ACS, creatinin elevation, sepsis etc. CK-MB can also increase in situations like fever, intramuscular injections.

Support vector machine

Machine learning, a branch of artificial intelligence, uses statistics and computer's calculation power for detection of complex pattern from data and rational decision making. Machine learning techniques have been successfully used for classification problems [11–14].

SVM, one of the machine learning techniques, was proposed by Vapnik, Lerner, and Chervonenkis. SVM is based on statistical learning and VapnikChervonenkis (VC) theorem. SVM is currently used in many fields with success [15, 16].

Linear separable SVM

Assume that m-dimensional x_i $x_i(i=1,\ldots,M)(x_i \in \Re^n)$ is in the trainingdata and the tags are $y_i=1$ Class 1 and $y_i=-1$ Class 2. If Class 1 and Class 2 can be linearly separable, the decision function of the separating hyperplane can be shown as $D(x)=w^Tx+b$, where w is the m-dimensional vector (normal) and $b$is the bias coefficient $(i=1,\ldots,M)$ [17, 18]. $x$is any point on the separating hyperplane and $|b|/\|w\|$ is the distance of separating hyperplane to the origin [15, 19]. The decision function should provide the inequations 1–2.

$$\text{Class } +1 \text{ if } wx + b \geq 1 \quad (1)$$

$$\text{Class -1 if } wx + b \leq -1 \quad (2)$$

These inequations are together expressed as in the inequation 3

$$y_i\left(w^T x_i + b\right) \geq 1 \quad i = 1,\ldots,M \quad (3)$$

An infinite number of decision functions can be produced in Fig. 1a. Here, the hyperplane with the largest border is defined as the optimal separating hyperplane (See. Fig. 1b) [15]. To find the separating hyperplane with a large border, the norm of w should be minimized. $\|w\|^2=\langle w,w\rangle$ is the product of $\langle .\ ,\ .\rangle$ points.

$$Min\ \frac{\|w\|^2}{2} \quad (4)$$

k.a.

$$y_i\left(w^T x_i + b\right) \geq 1 \quad i = 1,\ldots,M \quad (5)$$

The problem is a classical inequality constrained nonlinear optimization problem. The saddle-point solution of the lagrange function of the optimization problem can be found. The first rationale to use lagrange is to replace the constraints in inequality 5 with the constraints on the lagrangemultipliers that are simpler to cope with. The second rationale is showing the data only in the point multiplication form between the vectors while formulating the problem. [15].

Assessing the classifier performance

The classifier performance of four different methods (SVM, ANN, Naïve Bayes, andLogistic Regression)

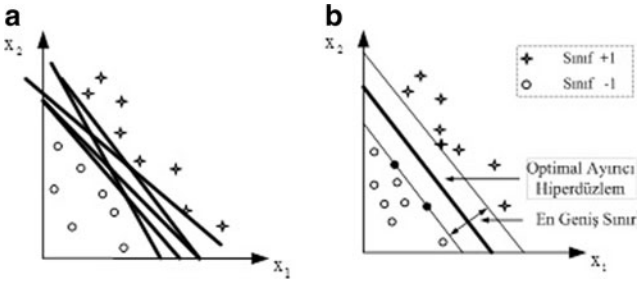

Fig. 1 (**a**) Linearly separable case, (**b**) Optimal separating hyperplane) [17]

was evaluated for the obtained trainingand testing samples. The evolution of the classifier performance was conducted using k-fold cross-validation. The prediction error was calculated by means of 5-fold cross-validation. The accuracy (the number of accurately classified positive or negative samples), sensitivity (True Positive rate), and specificity (False Positive rate) formulas are together expressed as in the inequation 6–10.

Formula of calculations

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP} \quad (6)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (7)$$

$$Specifity = \frac{TN}{TN + FP} \quad (8)$$

$$\text{Pr}ecision = \frac{TP}{TP + FP} \quad (9)$$

$$F\_Measure = 2 \times \frac{\text{Pr}ecision \times sensitivity}{\text{Pr}ecision + sensitivity} \quad (10)$$

The sensitivity is proportion of patients which detected positive via test to the whole patients. The specifity is the proportion of the patients which detected as normal via test to the whole normals. Accuracy is a measure which is free of errors (random and systematic). Precision is a measure of consistency of the test. F-measure is a measure of accuracy with the aid of precision and sensitivity.

Experimental study

In this section, presence of ACS was classified using linear SVM. In addition, the results were compared with ANN, Naïve Bayes, and Logistic Regression. In this study, we used a feed-forward ANN model composed of three layers: the input layer, the hidden layer, and the output layer. The input layer contains 7 neurons, the hidden layer 5 neurons, and the output layer 1 neuron. In the ANN used in this study a sigmoid transfer function was preferred, and tansig and purelin functions were used in the hidden and output layers. As there is not any hidden layer with an accepted number of neurons, these values were determined by the most appropriate error and classification success after a trial and error process. The predicting accuracy obtained with SVM, ANN, Naïve Bayes, and Logistic regressionwere shown on Table 4.

SVM has the highest predicting accuracy among the other methods (99.13 %). It is also followed by ANN and Logistic Regression methods with a high percent of accuracy 91.26 and 90.10 % respectively. The less accuracy belongs to Naïve Bayes with 88,75 %. Comparison of CPU training and test time is shown on Table 5.

Table 4 Comparison of classification accuracy

Methods	Predictingaccuracy (%)
SVM	99.13
ANN	90.10
NaiveBayes	88.75
LogisticRegression	91.26
Average	92.48

We found Logistic Regression had the lowest CPU time of test. The less CPU time of training is Naïve Bayes. The latency difference between SVM and Logistic Regression is 0.02 s. Train and test time is the slowest in ANN (26,24 and 0,15 s respectively). The best time in train is Naïve Bayes.

Five test were done for 5-fold cross validationand results of complexity matrix of SVM is given on Table 6. First test has a number of 46 patients. 25 patients has ACS positive and 21 patients are ACS negative. The algoritm detected all patients truly positive and negative. The second test has 46 patients with 24 ACS positive and 22 ACS negative. All patients were detected truly as positive and negative. However the third test has the same number of patients with 22 positive and 24 negative. The test detected 1 false negative. As well as third test, in fourth test with 46 patients of which half of them are ACS positive, the test detected 1 false negative. The fifth test has 44 patients with 20 ACS positive, 24 ACS negative. All patients were predicted truly as positive and negatives.

The accuracy, sensitivity, specifity, precisionand F-measure values are shown on Table 7

Predicted average accuracy of 5-fold-cross validation of SVM is found 99,13 %. Sensitivity and specifity is found 98,22 and 100 respectively. In the first test, all measures has 100 % of success. The second test also has also 100 % of sensitivity, specifity, accuracy, precision and F-measure. But

Table 5 CPU training and test time (the averaged CPU time in seconds, all experiments are carried out on a PC with Microsoft Windows 7 professional Intel (R) Core 2 Duo CPU E8200, 2.66GHz, and 3 GB memory)

Methods	CPU Time	
	Train	Test
SVM	0.13	0.10
ANN	26.24	0.15
NaiveBayes	0.10	0.09
LogisticRegression	0.11	0.08
Average	6.65	0.11

Table 6 Complexity matrix for SVM

Test	Predicted				
	Actual	P	N		Total
1	P	25	0	25	46
	N	0	21	21	
2	P	24	0	24	46
	N	0	22	22	
3	P	21	1	22	46
	N	0	24	24	
4	P	22	1	23	46
	N	0	23	23	
5	P	20	0	20	44
	N	0	24	24	

P positive, *N* negative

in the third test, accuracy and sensitivity has decreased to 97, 83 and 95,45 % due to the false negativity. The sprecifity, precision and F-measure had not changed. The fourth test has also decreasing accuracy and sensitivity (97,83 and 95, 45 % respectively) unlike specifity, F-measure and precision. The fifth test has a percent of 100 % success as well as the first and the second ones. Eventhough the average accuracy seems decreasing, it has a great percent of 99,13 %. Sensitivity of the test is 98,22. Precision, F-measure and specifity of the test is found 100 % due to no false positivity.

Discussion

Acute coronary syndrome is high mortality heart disease. Affected patients are heterogeneousand symptoms and signs are variable. While the therapy of STEMI consists of thrombolytic therapy or primary angioplasty, patients diagnosed with USAP may be hospitalized or discharged earlier. Treatment and follow up decisions aredepend on the clinical scenario and findings.

SVM is a machine learning technique which is commonly used in medical diagnosis. Especially diseases with a wide range of differential diagnosis, SVM is a high accurate method. It is used in diagnostic medicine, and high specifity and sensitivity of this method is reported in literature.

Techniques developed for diagnosing ACS should compile the most appropriate combinations of clinical data as well as results of ECG, laboratory, and imaging tests. The aim when establishing such techniques should be to discover the most logical and cost-effective technique. In the present study we developed a classification system to diagnose acute coronary syndrome using one of the machine learning, SVM, in patients presenting to emergency department with chest pain. Our results are quite interesting. The classification system with SVM and ANN have similarly higher success 99.13 and 90.10 % respectively.

Review of the outcomes in other studies are shown in Table 8. Green et al., in 2006, made ACS diagnosis with artificial nervous networks and logistic regression models. They found that, with ECG alone, ANN aggregates can predict ACS with an area under ROC curve of 80 %, sensitivity of 95 %, and specificity of 40 % [17]. We find ANN sensitive (90 %) similarly with literature but it was more specific (92.86 %) in our study.

In another study of SVM model, 242 chest pain patients categorized in AMI class or not, had an accuracy of 97,5 % with 10-fold-cross validation. We thought linear seperable SVM or the verification of cross validation model could make the difference of this success.[18].

Ho Ha et al. studied a model of SVM with a C5.0 algorithm and classified chest pain patients into three groups with variable tests of ACS, Troponin, CK-MB and CK. The groups are AMI, angina pectoris and other. Conversely our study, the study showed patients classification accuracy of ANN and SVM as 88,89 and 85,19 % respectively.[20].

Ghumbre et al. used a model of SVM and ANN, radial basis function and found 80,81 % accuracy. We thought about the difference due to usage of sigmoid transfer function which is more accurate (91,18 %) than the other study. Performance measure with 5-fold-cross validation has an accuracy of 85, 05 % with the same size dataset of our study. We think it is in consequence of not only the different function but also the

Table 7 Theaccuracy, sensitivity, specifity, precisionand F-measurevalues of SVM (%)

Test	Accuracy	Sensitivity	Specificity	Precision	F-Measure
1	100,00	100,00	100,00	100,00	100,00
2	100,00	100,00	100,00	100,00	100,00
3	97,83	95,45	100,00	100,00	100,00
4	97,83	95,65	100,00	100,00	100,00
5	100,00	100,00	100,00	100,00	100,00
Average	99,13	98,22	100,00	100,00	100,00
StandardDeviation	0,01	0,02	0,00	0,00	0,00

Table 8 Review of the outcomes with literature

	Classification Accuracy (%)	Sensitivity (%)	Specifity (%)
[Green et al.]	90.00	95.00	40.00
[Conforti et al.]	97.5		
[Ho Ha et al.]	88,89		
	85,19		
[Ghumbre et al.]	82,71	83,10	82,10
	85,05	84,05	85,90
Ourstudy	99.13	98,22	100

echocardiographic findings that we recorded [21]. Conversely SVM was compared to ANN about prediction of heart disease, ANN is found more accurate [22].

Among popular artificial intelligence studies, SVM was found more accurate than ANN in heart disease risk prediction. However accuracy of SVM is lower than we found (82 %). SVM is a kernel-based method and the accuracy can change due to the type of kernel function and variety of parametres [23].

Although the p values of CK-MB and troponin are insignificant in this dataset, the patients applying to emergency departments have these results of first application which makes the physician hard to decide to diagnose ACS or other reasons of this elevated results. Another aim of this study is to find out machine learning models' ability to help the physician with its prediction. SVM is more accurate for this study.

Imaging, laboratory and clinical scores are widely used in emergency departments. Although imaging and laboratory systems have a large widespread, bioinformatics will be taking their places. In emergency department, there are lots of differential diagnosis of chest pain. One of major mortal diagnose is ACS. Chest pain differs from patient to patient. Other diagnosis of chest pain can also affect ECG. Therefore it should be concretized by biomarkers and imaging techniques. CK-MB, CK and Troponin, ECG and echocardiographic imaging helps physician to diagnose or rule out. AlthoughACS is defined with ECG and biomarkers are also affected with other diagnosis, USAP has neither biomarker nor ECG positivity. As well as cut off levels of biomarkers have an important role, negativity of them can not rule out USAP. ECG findings, risk factors as smoking, hyperlipidemia, previous history of ischemia, ASA use, family history also help physician to score patient as high risk of ACS or not. Machine learning techniques have the true datasets of patients, and makes the decision fast and accurate. Even untrained staff can decide which patient have a high risk of ACS. Hence treatment or hospitalization can occur more rapidly. We choose patients with typical chest pain and their results are recorded. The outcome has been decided by emergency physicians and cardiologists with the aid of clinical scores like TIMI, GRACE and other supporting findings about ACS like high biomarker level. This makes the physician diagnose and hospitalization. This study suggested that support vector machine and artificial neural network may help emergency department staff make decisions by providing rapid results.

The limitations and conclusion of the study:

The diagnosis of acute coronary syndrome is made with patient history and findings on ECG. Due to the acute coronary syndromes are clinical, no angiographic findings were recorded and the diagnose were not verified by angiographic findings because of the "non-ACS" patients were not undertaken to angiography as well. Pain is a subjective definition. Many of the sufferers of "typical" chest pain may actually have learned their pain properties from internet or their previous admissions and use them for describing non-cardiac chest pain and mislead healthcare staff. Although patient defines his pain as typical, he has less risk of suspected ACS. In addition, chest pain suspected to originate from ACS were consulted with cardiology department and atypical chest pain presentations were excluded. The patients which hospitalized by the cardiology department with the diagnose of suspected ACS were labeled as "ACS present". Since the definitive diagnosis was put by history, ECG, laboratory, and echocardiography results, serial ECGs and cardiac enzyme results were disregarded. Superiority of risk factors of coronary artery disease to each other was not taken into account. Studies including more factors and patient data set are required to develop ancillary techniques with artificial intelligence techniques solely by using these parameters to decide admission or discharge of patients. *ACS* Acute coronary syndrome, *ECG* Electrocardiography, *SVM* Support vector machine, *ANN* Artificial neural network, *CAD* Coronary artery disease, *USAP* Unstable angina pectoris, *NSTEMI* Non-ST elevation myocardial infarction, *STEMI* ST elevation myocardial infarction, *TIMI* Thrombolysis In Myocardial Infarction, *GRACE* Global Registry of Acute Coronary Events, *EMMACE* Evaluation of Methods of Management of AcuteCoronaryEvents, *PURSUIT* Plateletglycoprotein IIb/IIIa in Unstableagina: Receptor Suppression Using Integrilin, *GUSTO* Global Utilization of Streptokinase and Tissue Plasminogen Activator forOccluded Coronary Arteries, *HR* Heart rate, *SBP* Systolicbloodpressure, *EF* Ejectionfraction, *CAD* Coronaryarterydisease, *ASA* Asetylsalisilicacid, *CK* Creatine kinase, *CK-MB* Creatine kinase-MB, *cTnt* Troponin T, *TP* True positive, *FP* False positive.

Compliance with Ethical Standards

Conflicts of Interest This study has no conflict of interest.

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