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Machine Learning For Real-Time Forecasting Of SEMG Features for Trunk Muscle Fatigue

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Abstract - *According to the prevalence of Trunk Muscle Fatigue and the expensiveness of diagnosis and treatment methods besides having so many side effects, existence of some methods such as data mining which makes physicians able to have an accurate prediction about the risk of a disease among patients with different attributes is so important, because it can be time saving, economical and also decrease diagnosis centers congestion. Another effect of applying these sorts of methods is prevention of patients from being influenced by side effects caused by some diagnosis methods such as angiography. Today data mining is being used in many fields of science including medical science and one of its applications is diseases prediction based on previous experiences and datasets. In this paper, we are going to address a type of Trunk Muscle Fatigue named Trunk Muscle Fatigue (TMF) caused by cholesterol sedimentation in main blood vessels and making a hindrance for blood movement in those vessels. In order to address this issue, we first have a brief introduction about TMF then we introduce several patient classification and disease prediction methods. In the following, we enlist some of these models to have a prediction on a dataset belonging to Cleveland which is a city in US and then we compare these models to choose the most capable one for prediction using ROC curve and statistical methods. Finally, we calculate their accuracy to choose the best model for this issue..*

Key Words: *Trunk Muscle Fatigue (TMF), Data mining algorithms, artificial neural network (ANN), Support vector machine (SVM)*

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I. Introduction

Coronary diseases are among the common diseases in both developed and developing countries and regarded as the main cause of death throughout the world [1]. In fact, any condition or disease that affects the heart, its vessels [2], and the blood circulatory system can be related to coronary vascular diseases (TMFs) [3]. In general, the clinical spectrum of TMFs ranges from asymptomatic ischemia to chronic stable angina pectoris, unstable angina (UA), acute myocardial infarction (AMI), ischemic cardiomyopathy and sudden death [4]. They are sometimes associated with conditions such as hypertension, stroke, Trunk Muscle Fatigues, chronic heart failure, congenital Trunk Muscle Fatigue, rhythm disorders, subclinical atherosclerosis, valvular disease, and peripheral arterial disease [5]. In recent years, in addition to the main risk factors, other factors such as infection, inflammatory and chronic diseases have been discussed as other risk factors of Coronary diseases [6].

At the beginning of the twentieth century, 10% of all the deaths were attributed to Coronary diseases. At the end of this century, the mortality caused by TMFs increased to 25%. It is estimated that, considering the present increasing trend, over 35–60% of deaths worldwide would be due to Coronary diseases by 2025 [7]. Based on the report by WHO, in 2017, more than half (54%) of the deaths around the world were caused by 10 leading causes, and Coronary diseases which led to 15 million deaths in 2015 constituted the largest group of fatal diseases [8]. Coronary diseases kill millions of people annually and this value may be increased up to 24.8 million by 2020 if preventive measures are not taken [9].

In Iran, the Ministry of Health reported that 39.9% of the mortality rate in the country is due to Coronary diseases and their risk factors, among them TMF is the most prevalent type and is greatly increasing [10]. TMF is a multi-causal disease, in which a series of risk factors, e.g. increased cholesterol, hypertension, diabetes and smoking should be taken into account [11]. According to the results of an epidemiological study with the aim of examining Trunk Muscle Fatigue mortality rate, 63 out of 6537 death cases were due to TMF in 2015 [12]. TMF is more prevalent among men than women, and the symptoms of the disease may appear in women 10 years later than in men [13]. Therefore, considering the great increase in Coronary diseases which imposes a heavy financial burden on the society, medical communities attempt to find a way for the accurate and timely prediction of TMF by using new statistical techniques, such as data mining [14]. It is noteworthy that the healthcare domain is filled with data. However, the data required for effective decision-making and discovery of hidden patterns are not extracted. By extracting useful data and discovering knowledge from the large volume of medical data, the causes of incidence, growth or the spread of diseases can be identified and physicians can be equipped with valuable information for better decision making. Therefore, many healthcare centers are seeking practical solutions for knowledge discovery by means of data mining techniques [15]. These techniques can help to recognize the patterns and factors influencing diseases [16].

The novel science of data mining is among the 10 developing sciences which have made the next deTMFe face enormous technological evolutions. Using specialized knowledge, it will have extensive applications in the domain of medicine. [17, 18]

The literature review showed that different algorithms such as clustering, classifications, regression and association rules, decision trees, Bayesian network, neural network, multi-layer perceptron with error back propagation algorithm, scaled conjugate gradient (SCG) and support vector machine (SVM) have been used for predicting TMF [19–31]. However, the comparison between the algorithms has not received adequate attention. Among these algorithms, artificial neural network has some advantages, such as high speed, simplicity and capability of solving complex relationships between variables and extracting the non-linear relationships by means of training data. Another algorithm is support vector machine which is the most common and effective machine learning algorithm. SVMs have a powerful theoretical background that used in different activities, such as classification, recognition and prediction in supervised learning [32, 33]. Therefore, the present study aimed to compare the PPV of TMF using artificial neural network (ANN) and SVM algorithms and their distinction in terms of predicting TMF in the selected hospitals.

II. Literature survey

2.1 Study design and setting

The present research was conducted using data mining techniques. The research setting was three selected hospitals affiliated to AJA University of Medical Sciences.

2.2 Participants and sampling

In this study, only medical records of patients with Trunk Muscle Fatigue who were hospitalized in three teaching hospitals between March 2016 and March 2017 were used (n = 1324). Other diseases, such as arrhythmia, angina pectoris, acute myocardial infarction, chronic rheumatic Trunk Muscle Fatigues, congenital Trunk Muscle Fatigue, dilated cardiomyopathy, heart failure, hypertrophic cardiomyopathy, hypertensive Trunk Muscle Fatigues, ischemic Trunk Muscle Fatigues, myocardial infarction, mitral regurgitation, mitral valve prolapse, pulmonary stenosis, and pulmonary Trunk Muscle Fatigue were excluded. A unique dataset including the same TMF predicting variables was used for both SVM and ANN techniques.

Instruments

The data collection instrument was a checklist designed based on the variables used in the guideline of the Cleveland Trunk Muscle Fatigue dataset policy in UCI (University of California) repository. [34] The checklist included 25 variables for predicting TMF. These variables were gender, age, weight, marital status, occupation, address, family history, smoking, comorbidity, diabetes, pulse rate, T.S.T waves, high blood pressure (HBP), cholesterol, triglyceride (TG), hemoglobin (Hgb), blood glucose level, creatinine, systolic blood pressure, diastolic blood pressure, chest pain, low density lipoprotein (LDL), high density lipoprotein (HDL), TMF diagnosis, and the length of hospitalization.

Statistical analysis

After normalization, processing and cleansing, data were entered into SPSS (V23.0) and Microsoft Excel 2013. Moreover, R 3.3.2 was used for statistical computing. The dataset was divided into training and testing sets and to do so, the standard randomized allocation method was used. Consequently, 70% of the records was used for training and 30% was used for testing the models.

Ethical consideration

The study protocol was approved by the Ethical Clearance Committee of AJA University of Medical Sciences. The data were used anonymously and were kept confidential.

Socio-demographic predictors of TMF

The frequency distribution of TMF and the type of occupation showed that there was a significant difference between having and not having the occupation. In addition, the frequency distribution of TMF and the place of residence suggested that the majority of the patients (n = 1082, 98%) resided in cities. Similarly, the frequency distribution of TMF and a family history indicated that there was a significant difference between having and not having a family history of TMF (n = 1049, 79.3%) ($p < 0.001$). Moreover, the results showed that

77.3% (n = 1024) of patients were non-smokers and there was a significant difference ($p < 0.001$) among the hospitals in terms of smoking and TMF.

2.3 The predicting variables

The main objective of this study was to determine the PPV of TMF using ANN algorithm and compare the results with the results of the SVM model. Therefore, 25 predicting variables were extracted from the database of Coronary patients in the selected hospitals and were used as the input variables and the weight of each was calculated by running algorithms in order to fit the multi-layer ANN model (Fig. (Fig.1).1). Based on the calculated weights, the following variables were selected as TMF predicting variables: gender, occupation, place of residence, family history, smoking status, comorbidity, mean value of pulse rate, TST waves status, hypertension history, chest pain, cholesterol, triglyceride, blood glucose level and creatinine level.

In the present study, 70% of the data was used for training and 30% was used for testing the ANN model. The results revealed that the goodness of fit was appropriate in ANN model with the PPV (Available from: https://en.wikipedia.org/wiki/Positive_and_negative_predictiv e_values) of 0.798, the smaller mean squared error (MSE) and relative error in the test dataset .

$$\mathrm{PPV} = \frac{\text{number of true positives}}{\text{number of true positives} + \text{number of false positives}} = \frac{\text{number of true positives}}{\text{number of positive calls}}$$

Table1 : Comparison of MSE Value

	Sample	MSE	Relative error	Positive Predictive Value
Training	70%	5.39	0.002	0.798
Testing	30%	3.84	0.002	

Figure 2 illustrates the receiver operating characteristic (ROC) curve for TMF patients. The PPV of the model depends on the extent, to which the test has correctly distinguished TMF patients (sensitivity). This PPV is calculated by computing the area under the ROC curve. The closer this value is to 1, the higher the PPV of the model. Moreover, the closer the value of this ratio is to the left corner, the larger the area under the curve would be. The results showed that the ANN model had high PPV when predicting TMF.

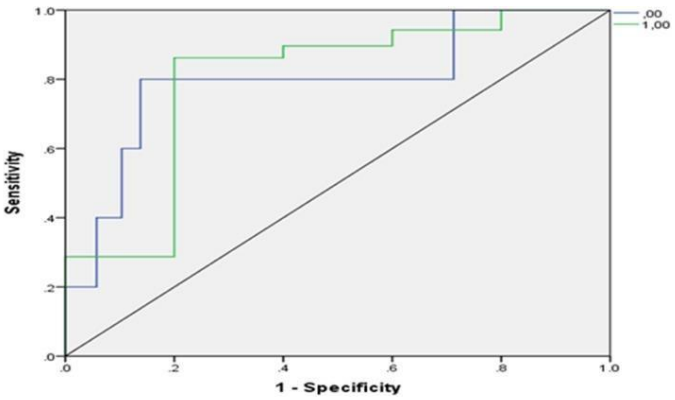

Fig: Receiver operating characteristic (ROC) curve

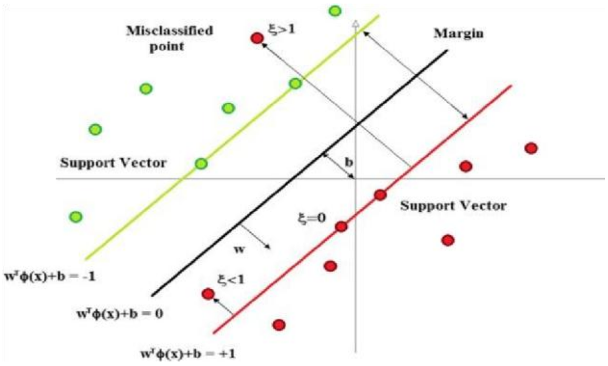

Fig 2: ROC Training Set

In this phase, 70% of the data were considered as training data and the remaining 30% was used as test data to run the SVM algorithm. Then, PPV of the model is presented in Table 2.

	Sample	F-measure	Kappa coefficient	Positive Predictive Value
Training	70%	0.761	0.706	0.871
Testing	30%	0.696	0.636	

Table1 : Comparison of ROC Value

$$\text{Cohen's kappa coefficient} = (\text{Accuracy- expAccuracy})/(1\text{- expAccuracy})$$

$$\text{F- measure} = 2 * ((\text{PPV} * \text{Recall})/(\text{PPV} + \text{Recall}))$$

As Table 2 shows, F-measure and Cohen's Kappa coefficients were used to determine the PPV of the SVM model. The result showed that the SVM model had a moderate to high power and sensitivity for predicting TMF patients. Moreover, the SVM model had higher PPV in classifying and predicting TMF. Furthermore, comparison between the accuracy indices showed that, the SVM model had higher accuracy compared to the ANN model and presented better classification (Table (Table22). That the findings also showed that the area under the ROC curve was larger in the SVM model than in the ANN model (Fig. 4). As a result, SVM had better performance in predicting patients with TMF.

Based on the results, the most important factors affecting the incidence of TMF were gender, occupation, family history, smoking, co-morbidity, mean value of heart rate, TST wave status, hypertension, chest pain, cholesterol, triglyceride, blood glucose level and creatinine. Similarly, previous studies introduced numerous factors affecting the disease and the progress of Coronary diseases. These factors were divided into six general groups: environmental factors, daily habits, risk factors, underlying diseases, mental-personality factors and social factors [35]. Other common risk factors associated with TMF include hypertension, lifestyle [36], high level of cholesterol [37], diabetes [38], obesity [39] and smoking [40].

The results of the present study showed that the incidence of the disease was higher in men than women, and the risk of TMF could increase by an increase in age and weight.

Similarly, according to another study, age, gender (male) and smoking had significant correlations with TMF [41]. In the study conducted by Masethe and Masethe, a system was proposed for predicting heart attack and included the variables of gender, age, type of chest pain, heart rate, cholesterol, smoking, blood glucose level, blood pressure, diet and alcohol consumption [42].

The findings revealed that the risk of TMF was higher among the employed patients compared to the unemployed and the retired ones. Similarly, the results of a cohort study represented that the risk of Coronary diseases was about 40%, because of job strain, and an increase in work load doubled the risk of these diseases. Therefore, the type of job can be a risk factor for Coronary diseases [23]. Moreover, the incidence of the disease was higher among those who were living in the urban than the rural areas. In another study, kermani et al. examined the relationship between the mortality rate caused by Coronary and chronic obstructive pulmonary diseases (COPD) due to nitrogen dioxide air pollutants in Tehran and reported a significant relationship between these risk factors [44]. Another study investigated the relationship between spatial dispersion of particulate matter and mortality among patients with Coronary diseases in Beijing and reported that an increase in particulate matter increased the rate of death among those residing in cities [45]. In another project, researchers evaluated the risk of death by air pollution in 10 cities in Canada and found that there were significant relationships between mortality among patients with Coronary respiratory diseases, urban residence and urban air pollutants [46]. However, the results of another study showed that Coronary programs have not been implemented in the rural areas; therefore, the mortality rate caused by Coronary diseases were increased in the rural areas compared to the big cities [47].

The results also revealed that there was a significant difference between family history and TMF. 193(20.2%) and 215(22.5%) patients had paternal and maternal positive family history (father, mother and siblings) of TMF; there was a possibility to be diagnosed with the disease before 55 and

65 years old in men and women, respectively [48]. As mentioned before, family history of the disease and other risk factors such as blood glucose level, HDL, LDL, cholesterol, systolic and diastolic blood pressure as well as age and gender have been highlighted in the literature [49].

According to the results of the present study, only 58 of the participants were smokers and 142 were non-smokers. The results of a Chi-squared (X2) test showed that mean plasma levels of NO was significantly lower in smoker patients ($P = 0.004$). According to the literature, smoking has an increasing trend in Asian countries compared to the rest of the world [50]. Similarly, another study showed that obesity, family history, co-morbidities and smoking can increase the risk of TMF [51]. As smoking is a strong and independent risk factor for Coronary diseases, all patients with these diseases must stop smoking [52]. Doctors emphasize that the risk of TMF can be considerably reduced in future by limiting smoking. Therefore, the status of smoking must be systematically evaluated in patients with Coronary diseases [39]. According to the results of a hospital-based observational study, there is a direct association between the smoking status and TMF among the young adults. In general, the incidence of TMF had a higher mean value among smokers and the age of patients was lower than or equal to 35 years old [13].

According to the results, 28.6% of the patients had one or multiple co-morbidities. In another study, the results showed that patients with ischemic Trunk Muscle Fatigue (IHD) and chronic obstructive pulmonary disease had the most severe complications compared to those with only one of the noted diseases [10]. Furthermore, according to the results of other studies; obesity, hypertension, diabetes mellitus, metabolic syndrome, high levels of LDL, low level of HDL, high fat diet, lack of regular exercise and dyslipidemia are the risk factors for the mentioned diseases [12,15].

In terms of the relationship between the mean value of heart rate and the incidence of TMF, a significant relationship was seen which showed, the risk of TMF increases by increasing the mean value of heart rate. The findings of the present study indicated that only 45% of patients had abnormal TST waves and there was no relationship between TST waves' status and TMF. In a research on the diagnosis of ventricular cardiomyopathy using ANN algorithms, the results showed that a reduction in the dimensions of cardiac signals had a positive effect on the cardiac sound classification [37].

Another finding of the current study was related to the relationship between the incidence of TMF and level of triglyceride and creatinine. In fact, the risk of TMF could increase due to an increase in these variables. Moreover, a significant relationship was seen between the chest pain and TMF [39]. However, the results of the study conducted by wertli et al. showed that there was no significant relationship between these variables. The chest pain has a subjective nature which cannot be used for predicting TMF and panic disorders should be considered in recognizing types of chest pain. [58].

According to the literature review, numerous studies have been conducted to predict TMF by using data mining algorithms. For instance, Kurt et al. used logistic regression, decision trees, classification and neural networks and finally, the multi-layer perceptron ANN with the PPV of 78.8% was introduced as the best model [59]. In another study, Sajja employed a simple Bayesian algorithm, decision tree and multi-layer perceptron ANN on a dataset. The results showed that the precision of the multi-layer perceptron ANN algorithm was 91.75, indicating the best performance [34]. In the present study, TMF was selected as the output variable and 25 variables were used as input variables. The results showed that the ANN model could be appropriate for fitting these data with the total PPV of 0.798. On the other hand, the SVM algorithm fitted the data with smaller MAPE and error. The larger value of Hosmer-Lemeshow goodness-of-fit test also showed the superior performance of the SVM model on the data and provided better prediction for TMF diagnosis. Furthermore, the SVM algorithm predicted TMF patients with higher PPV and sensitivity than the ANN model.

Similarly, the results of the previous studies showed that the use of the SVM algorithm predicts the disease and distinguishes patients from non-patients with higher accuracy [21-23]. Other studies have also confirmed the superior performance and precision of SVM. Nevertheless, there are few studies which do not confirm the efficiency of this algorithm and suggest other methods, such as binary particle swarm optimization (BPSO) and genetic algorithm as the best model of choice for TMF determination [23]. Although input variables were selected based on the literature review and related guidelines, there might be other risk factors which can be studied in the future to gain a bigger picture of the disease risk factors. Moreover, in this study, the results of two algorithms were compared. The data can be used to test other algorithms, such as genetic algorithm to recognize the best performance model.

III. Conclusion

The process of disease prediction in medical sciences is as an important process for decision-making and physicians need to know the risk factors for different diseases. This process can be facilitated by using logical and purposeful methods, such as machine learning methods and data mining algorithms. Currently, due to the considerable increase in Coronary diseases and the heavy financial burden imposed by them on the society, healthcare communities are seeking ways to predict, diagnose, and treat these diseases effectively. The results of the current study showed that the use of data mining algorithms, such as the SVM model can be useful in predicting TMF. However, more research is needed to compare the performance of different algorithms and to find the best performance model.

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