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Evaluation of several classification methods in carpal tunnel syndrome

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Abstract

Objective: To investigate the performance and effectiveness of 4 classification methods including support vector machine, naive Bayes, classification tree, and artificial neural network in the detection of carpal tunnel syndrome.

Methods: This retrospective study was conducted at Yuzuncu Yil University, Van, Turkey, and comprised record of patients suspected of having carpal tunnel syndrome between January and December 2013. The evaluations included age, gender, and 6 electromyography variables, including right/left median nerve sensory velocity, right/left fourth finger peak latency difference, and right/left median nerve motor distal latency. We investigated the performance of classification methods such as support vector machine, naive Bayes, classification tree and artificial neural network in the patients using data obtained from electromyography scan. A total of 6 criteria were used for the assessment of performance, including: true positive rate, false positive rate, true negative rate, false negative rate, accuracy, and preciseness.

Results: Of the 109 patients, 88(80.7%) were women and 21(19.3%) men. Besides, 67(61.5%) participants had carpal tunnel syndrome and 42(38.5%) did not have it. On classification tree, only 2 variables, i.e. left fourth finger peak latency difference and right/left median nerve sensory velocity, were found to be statistically significant ($p<0.001$). Naive Bayes had the highest detection score (91.04%), followed by support vector machine (89.55%).

Conclusion: Naive Bayes yielded better performance than all the other methods in the diagnosis of carpal tunnel syndrome, followed by support vector machine.

Keywords: Carpal tunnel syndrome, Entrapment neuropathy, Electromyography, Naive Bayes. (JPMA 67: 1654; 2017)

Introduction

Carpal tunnel syndrome (CTS) is the most common entrapment neuropathy. The statistical classification methods with binary variables such as patient/healthy and present/absent are also useful in the diagnosis of CTS. These statistical classification methods can be used with the data obtained from electromyography (EMG) scanning in the diagnosis of CTS.[1] The classification methods evaluated in the study included classification tree (CT), support vector machine (SVM), artificial neural network (ANN), and naive Bayes (NB). Assessment of the performance of these methods plays a key role in the establishment of the diagnosis of CTS.[2] The current study used two earlier instruments: a conventional logistic regression analysis and an artificial neural network to analyse data from 5,860 patients referred for diagnosis of hand symptoms. The combined instrument can be used as a preliminary screening tool for CTS, for self-diagnosis, and as a supplement to diagnosis in primary care.[3] That study further evaluated a computer-based infrared thermography (IRT) system, which employs artificial neural networks for the diagnosis of CTS using a large database of 102 patients. Compared with the gold standard electromyographic diagnosis of CTS, IRT cannot be recommended as an adequate diagnostic tool when exact severity level diagnosis is required. However, we conclude that IRT could be used as a screening tool for severe cases in populations with high ergonomic risk factors of CTS.[4] NB had a score of over 85%, both in accuracy and preciseness. The current study was planned to investigate the performance of classification methods such as SVM, NB, CT and ANN in CTS patients using data obtained from EMG scan.

Materials and Methods

This retrospective study was conducted at electroencephalogram (EEG)-EMG laboratory, clinical neurophysiology unit, Medical School Department of Neurology, Yuzuncu Yil University, Van, Turkey, and comprised record of patients suspected of having CTS between January and December 2013. The evaluations included age, gender, and 6 EMG variables including right/left median nerve sensory velocity (R/LMNSV), right/left fourth finger peak latency difference (R/L4FPLD), and right/left median nerve motor distal latency (R/LMNMDL).

SVM was first described by Vapnik in 1979 as a controlled method for the identification and classification of defect patterns. The primary aim in SVM is to construct a hyper

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plane. The patterns that lie on the edges of the hyper plane are called "support vectors". SVM makes use of kernel functions.[2] In this study, we used one of the most common kernel functions called "radial basis function".

ANN is a data-processing system mimicking human brain. In this system, neural networks perform complex functions simultaneously. A typical artificial neural network consists of three layers: input, hidden and output. Each nerve cell receives a signal from the input layer and processes it in the second layer which is connected with synapses and is known as the "network" and then sends it to the output layer via an activation function.[5]

CT is a nonparametric statistical method used for the determination of the relationship between a response variable and the other variables that may be related to the response variable. The topmost node in a classification tree is the root node. The classification starts with the root node and proceeds to the leaves that are most related to the response variable. The tree is repeatedly split into subsets. This process is repeated on each derived subset in a recursive manner. The process is completed when all the variables related to the response variable are arranged on the tree in a hierarchical manner.[5]

NB is a classification method used in data mining. NB is based on Bayes' theorem. In its simplest form, NB assumes that the occurrence or absence of a feature is independent of the value of any other feature given for classification. This assumption is called "conditioned independence".[5]

A total of 4 classification methods including SVM, ANN, CT, and NB were used in the study. To assess the performance of these methods, 6 criteria were used: True positive rate (TP) or CTS detection rate; False positive rate (FP) or false alarm ratio; True negative rate (TN); False negative rate (FN); Accuracy (AC); and Preciseness (PR).[5]

Results

The one hundred nine patients included eightyeight women and twentyone men. Mean age was 48.36±13.21 years in the patients with CTS and 38.71±10.66 years in the patients without CTS. No significant difference was observed between the patients with and without CTS with regards to all features except for R4FPLD ($p<0.001$) (Table-1).

Age, gender, and all the 6 electrophysiological variables were evaluated using Classification Tree (CT). On CT, only 2 variables, L4FPLD and L/RMNSV, were found to be statistically significant ($p<0.001$). Of these, L4FPLD indicated first-degree significance and CTS was detected in 56.7% of the patients with an L4FPLD value of "0". The prevalence of CTS decreased to 32.6% in the patients with an L4FPLD value of 0-0.55 and increased to 100% in the patients with an L4FPLD value of over 0.55. In the patients with an L4FPLD value of "0", L/RMNSV established a second-degree relationship with CTS. CTS was seen in 92.3% of the patients with an L/RMNSV value of fourtytwo or lower and in 29.4% of the patients with an L/RMNSV value of over fourtytwo.

Of the sixtyseven patients with CTS, sixty were correctly classified and 7 were wrongly classified by SVM. Similarly, fiftyeight out of the sixtyseven patients with CTS were classified as positive and 9 patients as negative.

Table-1: CTS and/or not in accordance with the status of descriptive statistics and comparison results.

	CTS	N	Average	Std. Dev.	Min.	Max.	p
Age	No	42	38,71	10,657	16	57	0,001
	Yes	67	48,36	13,231	18	78	
RMNSV	No	42	55,4619	5,29219	37,10	66,70	0,001
	Yes	67	45,2910	13,13862	,00	68,60	
LRMMNV	No	42	55,4643	6,36035	38,10	68,20	0,001
	Yes	67	44,8299	14,08656	,00	68,20	
RFFPLD	No	42	1,4857	8,50831	,00	55,30	0,451
	Yes	67	,6970	,72393	,00	2,90	
LFFPLD	No	42	,1524	,15099	,00	,50	0,001
	Yes	67	,6291	,61288	,00	3,10	
RMNMDL	No	42	3,0583	,46024	2,45	5,25	0,001
	Yes	67	4,0963	1,14589	2,60	8,20	
LMNMDL	No	42	2,8893	,44987	1,80	4,15	0,001

CTS: Carpal tunnel syndrome
N: Number of patient., Std. Dev.: Standard deviation., Min: Minimum., Max: Maximum., RDMSIH: RMNSV: right median nerve sensory velocity., LRMSIH: LRMMNV: Left/Right motor median nerve velocity., R4FA: RFFPLD: right fourth finger peak latency difference, L4FA: RFFPLD: left fourth finger peak latency difference., RMMDL: RMNMDL: right median nerve motor distal latency., LMMDL: LMNMDL: left median nerve motor distal latency.

Table-2: The value of the methods performance criteria.

	DP (%)	DN (%)	YP (%)	YN (%)	AC (%)	PR (%)
SVM	89,55	88,10	11,90	10,45	88,99	84,09
NB	91,04	83,33	16,67	8,86	88,07	85,37
CT	86,57	73,81	26,19	13,43	81,65	77,50
ANN	86,57	80,95	9,05	13,43	84,40	79,07

SVM: Support vector machine
NB: Naive Bayes
CT: Classification tree
ANN: Artificial neural network

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According to True Positive Rate (TP), NB had the highest score (91.04%), followed by SVM (89.55%). In addition, CT and ANN had the same scores. According to the True Negative Rate (TN), SVM had the highest score (88.1%), followed by NB (83.33%), ANN (80.95%), and CT (73.81%). ANN had the lowest score in False Positive Rate (FP) (9.05%) and NB had the lowest score in False Negative Rate (FN) (8.86%). NB had a score of over 85% both in Accuracy (AC) and Preciseness (PR), whereas CT had the lowest score in AC (Table-2).

These findings indicate that NB yielded better performance than all the other methods in the diagnosis of CTS, followed by SVM.

Discussion

CTS is often diagnosed based on the clinical findings; however, the use of EMG for the diagnosis of CTS is definitely recommended.[1] SVM, ANN, CT and NB are common classification methods that have recently been used in the classification of neurologic disorders.[6-10] This paper aimed to compare and contrast two types of models (logistic regression and decision tree induction) for the diagnosis of CTS using four ordered classification categories. Initially, we present the classification performance results based on more than two covariates (multivariate case). Our results suggest that there is no significant difference between the two methods. Further, we present a detailed comparison of the structure of bivariate versions of the models. The first surprising result of this analysis is that the classification accuracy of the bivariate models is slightly higher than that of the multivariate ones. In addition, the bivariate models lend themselves to graphical analysis, where the corresponding decision regions can easily be represented in the two-dimensional covariate space. This analysis reveals important structural differences between the two models.[11] A previous study used SVM and neural network (NN) in the classification of EMG findings obtained from patients with neuropathic and myopathic disorders and healthy individuals. The study concluded that SVM had a higher sensitivity in the diagnosis of neuromuscular disorders.[6] Another study used NN, SVM, decision tree (DT), and NB for the classification of the patients with juvenile myoclonic epilepsy and healthy volunteers by using the data obtained through EMG scanning. The study reported that DT, NN, and NB had a detection sensitivity of 100%.[7] SVM is a machine learning method commonly used with biomedical signal classification applications. In a study, a new particle swarm optimisation (PSO)-SVM model was developed that hybridised the PSO and SVM to improve the accuracy of EMG signal classification. All the experiments in the study were performed on the basis of EMG signal and the findings were classified as normal, neurogenic, or myopathic. The results obtained in the study confirmed that the SVM method was superior over conventional machine learning methods and suggested that the PSO-SVM classification system proposed in the study may provide further significant enhancements with regards to classification accuracy. The study concluded that the PSO-SVM system was proposed as an efficient tool so that various SVMs can be appropriately used as the core of PSO-SVM for the diagnosis of neuromuscular disorders.[8]

Another study suggested that the motor unit action potentials (MUAPs) in an EMG signal constitute a significant source of information for the evaluation of neuromuscular disorders. The same study used different types of machine learning methods to classify EMG signals and compared these methods in accordance with their accuracy in the classification of EMG signals. The study suggested that the EMG signals were automatically classified as normal, neurogenic, or myopathic in these methods. The comparative analysis conducted in the study showed the superiority of the fuzzy support vector machines (FSVM) modelling over the other machine learning methods in at least three points: slightly higher recognition rate; insensitivity to overtraining; and consistent outputs. The authors concluded that the FSVM model is a powerful model that can provide a reliable classification of EMG signals and assist the clinicians for making a correct diagnosis of neuromuscular disorders.[9] Sonomyography (SMG) refers to the monitoring of muscle contractions through the use of dynamic thickness changes in skeletal muscle during contraction and the use of ultrasound imaging. A previous study used ANN and SVM to estimate wrist angle from sonomyography by means of EMG signals. The estimations were conducted by using the thickness of extensor carpi radialis.[10] That study was aimed at comparing and contrasting two types of model (logistic regression and decision tree induction) for the diagnosis of CTS using four ordered classification categories. The first surprising result of this analysis is that the classification accuracy of the bivariate models is slightly higher than that of the multivariate ones. In addition, the bivariate models lend themselves to graphical analysis, where the corresponding decision regions can easily be represented in the two-dimensional covariate space. This analysis reveals important structural differences between the two models.[11]

Conclusion

NB yielded better performance than all the other methods in the diagnosis of CTS, followed by SVM. The use of EMG signals with reliable classification methods that assist the clinicians for making a correct diagnosis of CTS can be cost-effective and may enable early diagnosis of CTS. A correct diagnosis and the use of reliable methods are important factors that further empower the clinicians. Therefore, the correct assessment of statistical classification methods that provide high performance according to the given criteria is of prime importance. Accordingly, the studies to be conducted with this aim are likely to provide helpful information for future researchers and physicians.

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