Kafkas Univ Vet Fak Derg
25 (6): 741-747, 2019
DOI: 10.9775/kvfd.2018.21381

Kafkas Universitesi Veteriner Fakultesi Dergisi
ISSN: 1300-6045 e-ISSN: 1309-2251
Journal Home-Page: http://vetdergikafkas.org
Online Submission: http://submit.vetdergikafkas.org

Research Article

Classification of Biochemical and Biomechanical Data of Diabetic Rats Treated with Magnetic Field By PCA-Supported J48 Algorithm

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Article ID: KVFD-2018-21381 Received: 22.11.2018 Accepted: 05.07.2019 Published Online: 10.07.2019

How to Cite This Article

Pelit A, İbrikçi T, Özalp P, Taştekin B: Classification of biochemical and biomechanical data of diabetic rats treated with magnetic field by PCA-supported J48 algorithm. *Kafkas Univ Vet Fak Derg,* 25 (6): 741-747, 2019. DOI: 10.9775/kvfd.2018.21381

Abstract

The aim of this study was to investigate the J48 mediated decision tree algorithm from the principal component analysis - PCA, which is more complex, one of the statistical algorithms of diabetic metabolic disorders of Wistar albino rats' biochemical values and magnetic field application. Wistar Albino rats were examined under 4 different groups including the control group. When the results were examined, it was observed that PCA increased the success rate of classification from 96.25% to 97.50% when used with J48 decision tree algorithm. Thus, the PCA-supported J48 algorithm demonstrated that Wistar albino rats could be successfully used on the data obtained from more complex diabetic metabolic values.

Keywords: *Diabetes mellitus, Magnetic field, J48, PCA*

PCA Destekli J48 Algoritması İle Manyetik Alanla Tedavi Edilen Diyabetik Sıçanların Biyokimyasal ve Biyomekanik Verilerinin Sınıflandırılması

Öz

Bu çalışmanın amacı, Wistar albino türü sıçanların diyabetik biyokimyasal değerleri ve Manyetik Alan Uygulamasıyla kasılma değerleriyle daha karmaşık hale getirilen veri setinin, istatistiksel algoritmalarından biri olan temel bileşen analiz -PCA ile etkili karar ağacı makinesi öğrenme algoritması-J48 aracılığı ortaya konulmasıdır. Wistar Albino türü sıçanlarkontrol grubu da dahil olmak üzere 4 farklı grup altında incelenmiştir. Sonuçlar incelendiğinde, PCA'nın karar ağacı makinesi öğrenme algoritması J48 ile birlikte kullanıldığında sınıflandırmadaki başarı oranı %96.25'den %97.50'e arttırdığı gözlenmiştir. Böylece, PCA ile desteklenen J48 algoritmasının, Wistar albino türü sıçanlarının daha karmaşık hale getirilmiş diyabetik metobolik değerlerinden elde edilen veriler üzerinde başarılı bir şekilde kullanılabileceğini ortaya koymuştur.

Anahtar sözcükler: *Diyabetes mellitus, Manyetik alan, J48, PCA*

INTRODUCTION

Diabetes mellitus (DM) is a chronic autoimmune disease where either the pancreas does not produce enough insulin or the body cannot effectively use the insulin produced. Insulin regulates the blood sugar level by enabling entry of glucose into cells. Hyperglycemia or increased blood sugar is a common effect of DM leading to long-term vascular complications such as retinopathy, neuropathy and nephropathy [1]. There are essentially two types of DM. Type 1 DM usually results in the autoimmune-mediated destruction of pancreatic beta cells and absolute insulin deficiency. Type 2 DM is characterized by insulin resistance or relatively insufficient insulin release [2]. The number of people with diabetes has risen from 108 million in 1980 to 422 million in 2014 [3]. The global prevalence of diabetes among adults over 18 years of age rose from 4.7% in 1980 to 8.5 in 2014 [4]. In 2016, an estimated, 1.6 million deaths were directly caused by diabetes. Another 2.2 million deaths were attributable to high blood glucose in 2012 [5]. Almost half of all deaths attributable to high blood glucose occur before the age of 70 years. WHO estimates that diabetes was the seventh leading cause of death in 2016 [6].

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The muscles are the basis of the movement system. The fact that muscle diseases affect the quality of life in patients with and without diabetes is a condition that we all observe. Diabetes is a metabolic disease affecting various organ systems, including skeletal muscles. These changes are thought to involve both structural and metabolic defects. Experimentally induced diabetes is associated with changes in the contractile and electrical properties of skeletal muscles. The soleus and extensor digitorumlongus (EDL) are important skeletal muscles that play important roles in standing to the gravity force and exercises [7]. At the same time, atrophy may develop (muscle loss) in skeletal muscles and results in decreased muscle strength. The parameters are dependent on the distribution of muscle fiber types since the electrical and contractile functions of the skeletal muscles change. Therefore, the effect of diabetes mellitus on different skeletal muscles varies due to the distribution of muscle fibers [8].

There are many findings that electromagnetic waves have effects on organ systems, cell membranes and even the biological structure of enzymes [9]. Basset Previous studies have reported that magnetic field applications, which are used as a non-invasive method in the treatment of many diseases, may produce positive effects on different tissues [10-13]. It has been reported that low-frequency magnetic field applications help peripheral blood mononuclear cells to warn of diseases such as angiogenesis and diabetic foot ulcer [14]. Pulsed Magnetic Field (PMF) applications are considered to be a very important alternative treatment method for inflammatory pain resulting from pharmacological agents with toxicity and side effects [15-17]. It has been observed in research that PMF has an effect on healing in neuropathic pain induced by diabetes PMF application increased regeneration by approximately 22% after sciatic nerve crush injury [18,19]. We can easily say there is a relationship between diabetes and muscle strength and between muscle strength and the magnetic field [18].

In order to research diabetes and its complications of DM, we need to have advanced information technology. Therefore, data mining technology is an appropriate study field for us. Data mining, also known as Knowledge Discovery in Database, is defined common study as the computational process of discovering patterns, large dataset involving methods of artificial intelligence, machine learning, statistics, and database system [20]. Recently, Zou and co-workers reported that Support Vector Machine (SVM), Decision Trees (DT) are the most common classification tools for predicting diabetes. The j48 algorithm is one of the most successful algorithms used in DT classification [21]. Models are also based on the baseline estimates of medical decision-making systems in diabetes diagnosis. They are based on the underlying statistical analysis of the results of studies and are thus more meaningful in relation to the outcome. For high accuracy of forecasting success, it is necessary to create the best model using headed algorithms.

In this study, Wistar type albino rats were used for experiments. Biomechanical, biochemical values, body weights, and other parameters were measured in the all group end of the experiments. Based on these parameters data mining was used in this research. Data mining, decision tree and j48 algorithms with the help of machine learning through the data provided by diabetes classification were made. J48 algorithm was utilized from decision tree algorithms including 7 attributes. Then, attribute selection (PCA) was chosen for just three attributes, and the results were compared with these three attribute values. Using the data obtained from the experimental rats, machine learning and estimation were applied to the computer with the help of DT and J48 Algorithms, then, it was aimed to compare the data obtained from the experiment with the data obtained as a result of machine learning.

MATERIAL and METHODS

The ethics committee approval was provided from Animal Experiments Domestic Ethic Committee of Çukurova University (No. B.30.2.ÇKO.0.5L.00.001). The model organisms studied were Wistar albino rats. Wistar Albino rats were examined under 4 different groups including the control group: Group I (n=20, control), Group II (n=20, control with magnetic field), Group III (n=20, streptozotocin-induced diabetes), and Group IV (n=20, streptozotocin-induced with magnetic field), where *n* denotes the number of rats in each group. We have recorded the animals' weight (*g*), biomechanical and biochemical parameters. Biomechanical parameters included twitch and tetanic parameters. Twitch (mN/mm^2) is a mechanical reaction to a solitary incitement of the muscle. Tetanic contraction force (mN/mm^2) is created at a high rate by a solitary muscle unit. Biochemical parameters included blood glucose level (in mg/dL; the ordinary estimate for rodents is under 300 mg/dL, and greater than 300 mg/dL is called diabetic), high density lipoprotein (HDL; in mg/dL), low density lipoprotein (LDL; in mg/dL), and triglyceride (in mg/dL). Blood glucose level is the measure of glucose exhibited in the blood of people and different creatures. HDL is known as the "good" cholesterol since it conveys cholesterol from different parts of the body back to the liver. The liver at that point expels the cholesterol from the body. LDL is known as the "bad" cholesterol on the grounds that a high LDL level prompts development of cholesterol in the supply routes. Triglycerides are the most widely recognized form of fat in the body; they store overabundant calories from the dietary regimen. A high triglyceride level conjoined with low HDL cholesterol or high LDL cholesterol is connected with fat accumulation in blood vessels. This increases the risk of heart attack and stroke.

Magnetic Field Application

The MF was created by a couple of 60 cm-wide Helmholtz curls that were 30 cm apart. The loops were placed in a 90-90-50 cm-sized Faraday confine to forestall natural electromagnetic collaboration. Helmholtz curls were associated with a power supply and a chip-controlled recurrence generator created by the Department of Biophysics, Çukurova University, Adana, Turkey. For estimating the force of the MF, a pivotal test of a Tesla Meter (PHYWE System GmbH, Gottingen, Germany) was placed inside the MF confine. MF power was 1.5 mT, and there were no temperature changes caused by the MF. The rats were placed into a 30-30-25 cm plastic cage between the two curls where they could roam freely. The introduction was connected for a month for Groups II and IV. Five experimental animals were placed within MF exposure inside this cage, exposure was invariably applied to separate regions, excluding groups I and III. Therefore, the animals were not exposed to electrical transitions once the sphere was turned on and off.

Biomechanical Recordings

After 30 min of thermoregulation and equilibration, the muscle length was resolved (the length provides the most extreme muscle strain). Amid the entire preliminary timeframe, the muscles were specifically fortified for 20 min supramaximally by applying square frequencies of 0.05 Hz (15-20 V) of 0.5-ms intervals. To fortify the muscle and to record the reaction, a force-displacement transducer (FDT 10-A 500 g, Commat, Ankara, Turkey), a stimulator (STPT02-A, Commat), an exploratory tissue organ bath and circulator (WBC 3044, Commat), and the Biopac Systems (Goleta, CA) Student Lab System (MP30) were utilized. The muscle strain (Ps; in mN/mm^2), contraction times (CT) and half-relaxation times (HRT, in ms), and the contraction and relaxation rates (±dP/dt; mN/mm^2. ms) were recorded. After utilization of the beat trains of 10, 20, 50, and 100 Hz frequencies for times of 200-400 ms, the greatest muscle strain was recorded. These parameters were repeated for every one of the groups (I-IV). The muscle cross-sectional zone was evaluated utilizing muscle weight and length. The length was estimated before the distal ligaments were cut.

Principal Component Analysis (PCA)

One of the data pre-processing methods before the use of machine learning is the PCA [22]. The aim is to discover variables that best represent the data; with fewer variables, PCA is a useful statistical technique for understanding the relationship of multiple dimensions during data analysis and, thus reduces the size of the data set (dimension reduction). At the same time, intensive clustering in data mining can also result in more rapid processing of some operations (e.g., training of the classification algorithm) by converting a dataset with n features into a *k* (k<n) dimensional dataset.

Clearly, some of the features of the data will be lost during these operations since the PCA can also clarify the data sets and the relationship of the data to each other, so the data can also be used to calculate the weights of the effects. The major aim is to be able to work with a minimum loss by maintaining high variance.

Decision Tree -J48

The J48 decision tree, also known as C4.5, is an alternative Dichotomizer-3 (ID3) -based machine learning model which is based on the Quilan side; the model identifies and predicts a target value (dependent variable) of a new instance based on the various property values of the existing data J48 [23]. It is quite a popular algorithm that is ranked #1 in "top 10 algorithms in data mining" [24].The decision tree classifier follows a simple divide-and-conquer algorithm. To classify a new substance, it is first necessary to form a decision tree based on the property values of the existing training data. For this reason, when compared to the number of items (training set), the nature that distinguishes the various examples is clearly determined. Different attributes of a decision tree define the final value (classification) of a dependent variable in nodes, while branches between nodes report the possible values that these attributes may adopt in the observed instances. The property to be estimated is known as the dependent variable because the value depends on the values of all other properties or is related to the values of all other properties. Other features that assist in predicting the value of the dependent variable are known as arguments in the data set.

Model Evaluation

Root mean square error (RMSE), mean absolute error (MAE), RRSE are regularly employed in model evaluation studies. Experimental results are evaluated for both precision and accuracy, in medical data, it is common to express accuracy as a percentage. While magnetic field application made the data set more complex, PCA was applied to reduce the data.

Accuracy = (correctly predicted class /n) × 100% (Equation 1)

The Kappa test is presently a standard statistical method that measures the reliability of fit between two or more classes. The Kappa value ranges between (-) 1 and (+) 1, the positive value is shown as better interpreted, and kappa values between 0.81-1.00 indicate a very good level of integration.

When the results are examined, it is seen that the PCA increases the success rate in the tree learning algorithms from the machine learning models in this study. It has been observed that the J48 algorithm improves accuracy when used together with PCA. In the Kappa (K) values, the Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Relative Absolute Error (RAE) and Root Relative Squared Error (RRSE) values were also found to improve.

The formula of K is given Equation 2.

$$K = \frac{\Pr(a) - \Pr(e)}{1 - \Pr(e)} \qquad \text{(Equation 2)}$$

The MAE shows thatthe average of all absolute errors and is a linear scoring that means that all individual differences are equally weighted in the mean. The formula is given in Equation 3.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |actual - predicted| \qquad \text{(Equation 3)}$$

Where n = the number of errors, |actual – predicted| = the absolute errors.

The RMSE should be scored on the second level. which this metric measures the difference between the actual value and the predicted value. The formula is given in Equation 4.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(actual-predicted)^2}{n}} \qquad \text{(Equation 4)}$$

The formula of RAE shows the absolute error of the size of the thing being measured. The formula is given in Equation 5.

$$RAE = \frac{\sum_{i=1}^{n} |actual-predicted|}{\sum_{i=1}^{n} |Ave-predcitedæ} \qquad \text{(Equation 5)}$$

TheRRSE is relative to what it would have been if a simple predictor had been used. More specifically. this simple predictor is just the average of the actual values. The formula is given in Equation 6.

$$RRSE = \sqrt{\frac{\sum_{i=1}^{n}(Actual-predicted)^2}{\sum_{i=1}^{n}(Average-predicted)^2}} \qquad \text{(Equation 6)}$$

RESULTS

J48 classification involves a classifier based on 7 attributes and 4 groups, using J48 as the algorithm, and classifies the muscle contraction parameter by considering the magnetic field specifier in the J48 algorithm. Ten-fold cross-validation mode was used for classification. In terms of data obtained from the diabetic group, it was determined that measured glucose levels were high. The reason for increased glucose levels in diabetic animals was that, in this study, rats were injected with a single high dose of 45 mg/kg/mL STZ (i.v.), which might disrupt the function of the insulin-releasing mechanism according to the widely accepted view of scientists [25-27]. No enhancing treatment was applied to animals for 30 days. All data sets were given in *Table 1*.

Furthermore, the blood glucose levels for diagnosing diabetes in humans during fasting and 2 h postprandial are 7.0 mmol/L (126 mg/dL) or greater and 11.1 mmol/L (200 mg/dL) or greater [28], respectively, and the situation for diabetic rats is that they can be considered as diabetic with blood glucose levels of 300 mg/dL (16.7 mmol/L)[7]. The J48 algorithm used the Twitch (mN/mm^2) feature to classify the data in the set. The values of isometric twitch were <= 45.47 (mN/mm^2) according to the values of Group III and Group IV, and isometric twitch values > 45.47 (mN/mm^2) were classified as Group I and Group II *(Fig. 1* and *Table 2)*. Classification of the J48 algorithm according to the contraction parameters which are magnetic field indicator was defined by these methods. Using PCA, a wider range of variance was generated using the entire data set. The resulting three new features using the J48 algorithm in the new dataset are provided in *Fig. 2* and *Table 3*.

DISCUSSION

Diabetes mellitus is a disease with a wide range of social effects including muscular and neuromuscular diseases such as muscular atrophy and partial paralysis; therefore, it is a

Table 1. *Basic descriptive statistics organized by groups*

Groups (n=20)	Parameter	Weight (g)	Glucose (mg/dL)	HDL (mg/dL)	LDL (mg/dL)	TG (mg/dL)	Twitch (mN/mm^2)	Tetanic (mN/mm^2)
Group I	Std. Dev.	11.76	2.36	1.25	0.58	1.40	0.51	2.92
	Min.	322.72	160.08	35.57	15.22	70.97	45.62	199.38
	Max.	354.94	167.06	39.43	17.08	75.05	47.26	208.18
	Arith. Mean.	338.36	163.652	37.697	16.12	73.06	46.35	203.26
	Std. Error	2.70	0.52	0.28	0.13	0.31	0.11	0.65
Group II	Std. Dev.	14.63	4.11	1.03	0.51	2.45	0.48	0.72
	Min.	276.41	148.65	36.08	13.77	47.89	51.33	218.22
	Max.	324.68	161.08	39.37	15.23	54.41	52.89	220.83
	Arith. Mean	293.48	155.41	37.78	14.61	51.41	52.13	219.93
	Std. Error	3.27	0.92	0.23	0.11	0.55	0.10	0.16
Group III	Std. Dev.	4.71	7.66	1.55	2.49	8.79	0.23	0.47
	Min.	293.69	584.32	42.63	65.15	245.56	41.02	93.65
	Max.	308.19	610.64	47.27	72.77	271.18	41.76	65.32
	Arith. MeanStd.Error	300.40	597.28	44.40	68.36	259.78	41.40	94.608
		1.05	1.71	0.34	0.55	1.96	0.05	0.10
Group IV	Std. Dev.	1.65	10.30	1.23	1.07	7.53	0.38	1.19
	Min.	301.41	550.17	41.22	53.13	162.68	44.31	147.7
	Max.	306.55	579.24	45.03	56.65	184.66	45.47	151.91
	Arith. Mean.	304.11	567.71	42.99	55.05	173.56	44.98	150.30
	Std. Error	0.37	2.30	0.27	0.24	1.66	0.08	0.26

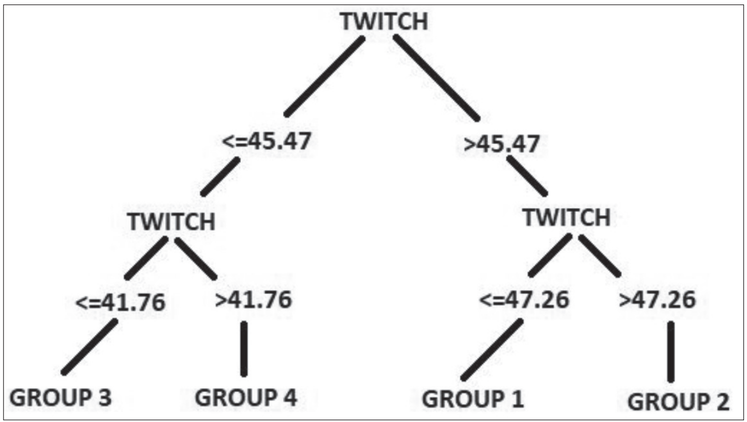

Fig 1. Decision Tree Classification, J48 algorithm in the four groups; It has been classified as to the twitch attributes. (WEKA Version 3.9.2)

Table 2. *Biomechanical parameters for all groups with Decision Tree Classification*

Muscle Contraction	<= 45.47	Twitch > 45.47
Twitch (mN/mm²)	<= 41.76; Group III (20.0)	<= 47.26; Group I (20.0)
Twitch (mN/mm²)	> 41.76; Group IV(20.0)	> 47.26; Group II (20.0)

Fig 2. By decreasing the attributes to PCA with 3-attributes

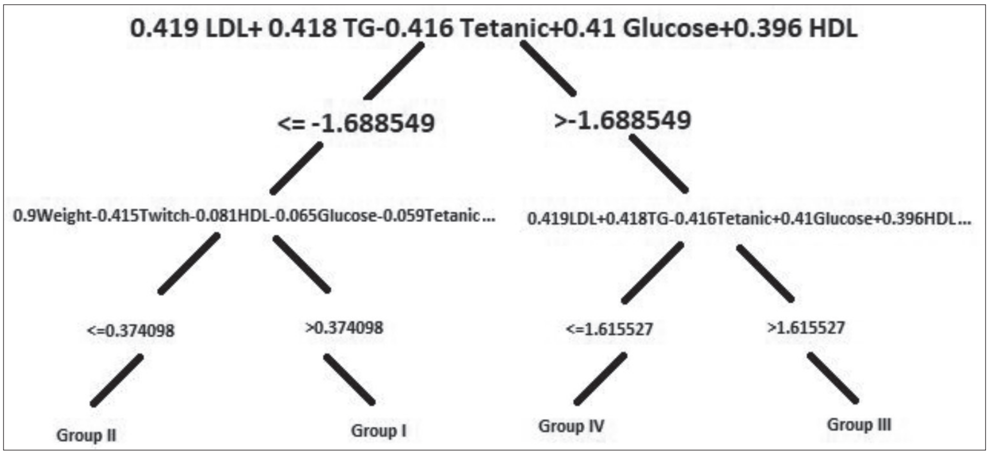

Table 3. *The performance results of J48 Algorithm applied with PCA and without PCA*

Total Number of Ins. =80	Correctly Classified Ins.	Accuracy (%)	Kappa Statistic	Mean Absolute Error (MAE)	Root Mean Squared Error (RMSE)	Relative Absolute Error (%) (RAE)	Root Relative Squared Error (%) (RRSE)
Without PCA	77	96.25	0.95	0.0187	0.1369	5	31.62
With PCA	78	97.50	0.96	0.0125	0.1118	3	25.82

priority in many studies including machine learning and data mining studies. We have applied a controlled learning algorithm in our categorization model because the value of the dependent variable or output variable was estimated through a set of inputs or independent variables. Support Vector Machine (SVM), Artificial Neural Network (ANN) and DT are the most commonly used classification algorithms used in estimation methods, as mentioned in the literature. Generally, controlled learning algorithms and the rules of the relationship between biomarkers are discussed in approximately 85% and 15%, respectively, of DM estimation studies [29]. Numerical results were obtained in parallel with the same classification methods used in DM studies.

Biochemical and biomechanical measurements developed with diabetes model were generated by the hypothesis that variables are related to the PCA of each other, a hypothesis that could be used in data preparation techniques for analyses. These measurements were preferred for the destruction of the dependency structure or for size reduction [30,31]. PCA and Machine learning techniques are known in previous studies for their use in a large number of complex data. In this study, we found that PCA and J48 algorithm can be possible with a limited number of subjects in large and complex data. We believe that this algorithm will increase the accuracy percentage in a high number of subjects. In our study, although the number of rat subjects was limited due to ethical reasons, biochemical parameters and magnetic field factor were 7 attributes in 4 different groups forming the data set. In fact, Wu et al.[32], using the Weka algorithm in the predictive model of diabetes, Artificial neural networks with J48 and ID3 compared with 89.3%-81.9% showed that they work with higher accuracy. They found that the use of different pre-processing techniques in DM prediction modeling increased accuracy in Bayes and DT classification.

We could compare our results with Quan Zou et al.[21]'s results that they applied many machine learning algorithms on public diabetics datasets. They showed that J48 was 74.75% accuracy on Pima Indian's dataset. But, J48 gives better accuracy results on our dataset.

Diabetes mellitus is a major public health problem allover world. In this study, we applied PCA and J48 two different algorithms in models for predicting diabetes mellitus using 7 important attributes biomechanic and biochemical of the four groups classified by twitch attributes. We may conclude that *Table 3* demonstrates that applying PCA with J48 has increased the predictive success of the diabetic studies that the incremented of accuracy is 0.75% when we compared them with or without PCA. However, this is a significant increment on biological datasets. Therefore, it is shown that J48 could be applied to this kind of biological datasets with PCA.

Although there are constraints (number of subjects, diabetes) in animal experiments, the results are confirmatory to our hypothesis. If the same data set is obtained on people, it is thought that a higher performance rate will be achieved.

Conflicts of Interest

The authors declare no conflict of interest.

Acknowledgments

The samples used in this study are data collected from the project supported by Çukurova University Scientific Research Foundation (Project no. S.B.E. 2002. D27).

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