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ARAŞTIRMA MAKALESİ

Biyomekanik Özellikler Yardımıyla Düşme Riski İçin Bir Karar Destek Sistemi: Çarpıcı Uygulama

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Anahtar kelimeler
Denge;Entropi; Veri madenciliği, Karar ağaçları; Düşme riski.

Özet

Düşme ve düşmeden kaynaklı yaralanmaları önlemek için aktif insanların düşme riskini değerlendirecek yeni araçların geliştirilmesi gereklidir. Bu makale, hangi parametrelerin düşme riskinde ve risk düzeyinde etkili olduğunu incelemeyi ve böylece de bir algoritmayı geliştirmeyi amaçlamaktadır. Bu amaçlara ulaşmak için, çok sayıda değişkeniirdeleyerek, yalınbir algoritma üretilmiştir. Bu algoritma karar ağacı ve entropi üzerine kurulmuştur. Bu algoritmayı üretmek için, 24 gönüllü ve 46 adet düşme riskinin değişkeni kullanılmıştır. Kikare analizi sonuçlarına göre; fizyoterapistin muayene teşhisi sonuçları ile algoritma sonuçları arasındaistatistiksel olarak anlamlı ilişki bulunmuştur($p<0.001$ ve kappa=0.852).Geliştirilen sistem,kısa süreli bir eğitim ile klinisyen/klinisyen olmayan kişiler tarafından kullanılmak üzere tasarlanmıştır. Sonuç olarak, var olan verilerimiz sınırlı olmasından dolayı, bu algoritmayı yaygın klinik/klinik dışı kullanım için önermeden önce farklı özelliklere sahip daha geniş bir popülasyonda test edilmelidir.

A decision support system for fall risk through biomechanical characteristics: A strikingapplication

Keywords

Balance; Entropy; Data mining; Decision tree; Fall risk.

Abstract

Evaluation of new tools to assess the risk of falling for active people is needed to help prevent falls and fall-related injuries. This article aims at investigating which parameters are effective at fall risk and level of the risk, and thus at developing an algorithm. To achieve these aims, an algorithm has been produced by taking into consideration a wide number of variables and simplicity. This algorithm has been based on a decision tree and entropy. To produce this algorithm, 24 subjects and 46 variables of fall risk were used. In the chi-square analysis carried, it is found a statistically significant relation between the computed results and examination results of physiotherapist ($p<0.001$ and kappa=0.852). Our tool has been designed for use by clinical/nonclinical care professionals with a minimum of training. As a conclusion, before recommending this algorithm for widespread clinical/nonclinical use, it should be tested in a wider population with at least more different characteristics from the current sample.

1. Introduction

Fall risks are growing concerns in all societies (e.g., Panel on Prevention of Falls in Older Persons, American Geriatrics Society and British Geriatrics Society, 2011). Evaluation of new tools to assess the risk of falling for active people is needed to help prevent falls and fall-related injuries. These tools are expected to be used by any health care provider, and not be time consuming. The effective tools are also expected to differ from others primarily by its relative simplicity, both in the number of items and their measurement. In this respect, there are various studies to assess fall risk in the literature (Lajoie*et al.* 2002, Keskin*et al*. 2008,Bongue*et al*. 2011,Rueangsirarak*et. al.* 2012).

The developed algorithm has been designed under the expectation of use by clinical and nonclinical care professionals, particularly suited to primary care. This article aims at investigating which parameters are effective at fall risk and level of the risk, and thus at developing an algorithm. To achieve these aims, we produced an algorithm taking into consideration a wide number of variables and simplicity. This algorithm is based on decision tree and entropy.

Since 1970s, researchers have paid their attention to machine learning specifically decision tree algorithms such as ID3 (Iterative Dichotomiser) (Quinlan, 1994). This work is an expansion of an earlier work on concept learning systems by Hunt *et. al*. (1966). Quinlan (1994) later produced C4.5 which is a supervised learning algorithm. A group of statisticians Breiman*et. al.* (1984) published the book Classification and Regression Trees (CART), which described the generation of binary decision trees. The two similar approaches for learning decision trees ID3 and CART were invented independently of one another at around the same time. ID3, C4.5, and CART adopt a non-backtracking approach in which decision trees are constructed in a top-down recursive divide-and-conquer manner. Many algorithms for decision tree induction also pursue such a top-down approach, which commences with a training set of tuples and their incorporated class labels.

2. Material Methods and Study Design

Our work group consists of twenty-four subjects (19 subjects, 5 healthy subjects; 8 females, 16 males) from the Dumlupinar University Hospital, Physical Therapy and Rehabilitation Department. Eighteen subjects are non-smoking, 4 subjects are smoking and 2 subjects stopped smoking, and in total 24 subjects. Three subjects have cardiovascular disease, one subject has pulmonary disease, five subjects have musculoskeletal disease, one subject has got both cardio-vascular and pulmonary diseases and nine of the subjects have all the diseases. The exclusion criteria for all subjects included plantar ulcers at the moment of the evaluation, vision impairment, use of a walking stick, peripheral vascular disease, vestibulopathy history, any neurological disease, muscular disease, rheumatic disease, the diabetes etiology, history of abusive alcohol intake, and partial or total amputation. The study had local research and ethics committee approval, and all participants gave written consent.

Falls are a vitally important health issue for adults especially for elderly people. The literature tells us that there are more than 130 risk factors encountered in various studies. The fall risk factors commonly identified are use of psychoactive medication, use of a walking aid, fear of falling, being female sex, older age, use of multiple medications, gait instability, fear of falling, decline in activities of daily living, etc. (Gates *et al.* 2008, Kwan *et al.*2011).

Several performance balance measures, such as one-leg stand (OLS), functional reach (FR), Tinetti balance and Berg balance scale are available in the literature e.g. in (Lin*et al.*2004). However, it is time-consuming to use all of these measures for each individual, and each of them may not be appropriate for every subject. As pointed out in the literature e.g. in (Michikawa *et al.* 2009), the one-leg standing (OLS) test is preferred in the present study since it has conventional advantages such as: inexpensive, time-efficient, easy to perform for both examiner and examinee, and it does not require use of special equipment.

2.1.One-Leg Standing Test

The OLS tests were measured on dominant and non-dominant legs in three positions: eyes open (60 s), eyes closed (30 s), and eyes open, with head rotation (30 s) with arms held comfortably at the side. Participants were allowed one practice trial for each of the balance tests. Each participant performed three trials, and the best result of the three trials was recorded (Lord *et al.* 1999, Huang *et al.* 2003, Cimbiz and Cakir 2005).

2.2.Functional Reach Test

The subject must be able to stand independently for at least 30 seconds without support and be able to flex the shoulder to at least 90 degrees. A 90 cm stick is attached to a wall at about shoulder height. The subject is positioned in front of this so that upon flexing the shoulder to 90 degrees, an initial reading on the stick can be taken. The practitioner takes a position 150-300 cm away from the subject, viewing the subject from the side. Older subjects should be able to move the forward at least 15 cm (Hurvitz *et al.* 2000, Huroyuki *et al.* 2003, Ozdirenc *et al.* 2003).

2.3.Measurement of Current Perception Threshold

Current perception threshold (CPT) measured are objective, determinations of sensory nerve conduction and functional integrity which are obtainable from any cutaneous site by using electrical stimulation (Ciaramella*et al.* 2013). Endomed 980 electrical stimulation tool was used to assess the CPT. Square wave form of galvanic curve with 1 ms impulse duration, 5ms interval and 166 Hz frequency was used for the assessment. An active pen electrode was placed on the five metatarsal joints, heel and lateral side of the foot for both dominant and non-dominant legs of each subject (totally 7 various points). A passive electrode was placed to below knee on fibular side and then electrical stimulations were applied between the active and the passive electrodes. Subjects were positioned in a long sitting position without footwear. The intensity of current was increased gradually and subjects were asked to report to physical therapist when they first felt the current. The current intensity which the subject first felt was recorded as sense threshold. The results were recorded in milliampere. The measurements were repeated three times by the same physical therapist and the average of three measurements was recorded (Pitei*et al.* 1994, Matsutomo *et al.* 2005).

2.4.The Decision Tree Introduced by Using Entropy

ID3 uses information gain as its attribute selection measure. This measure is based on a remarkable work of Shannon and Weaver (1949) on information theory. Let node N indicates the tuples of partition D. The attribute with the highest information gain is chosen as the splitting attribute for node N. This attribute reduces the information needed to classify the tuples in the resulting partitions and reflects the least randomness in these partitions. Such an approach minimizes the expected number of tests needed to classify a given tuple and assures that a simple tree is found. The expected information needed to classify a tuple in D is given by

$$Info(D) = -\sum_{i=1}^{m} p_i \log_2(p_i) \qquad (1)$$

where p_i is the probability that an arbitrary tuple in D belongs to class C_i and is estimated by $\frac{|C_{i,D}|}{|D|}$. Since the information is encoded in bits, a log function to the base 2 is used. $Info(D)$ stands for the average amount of information needed to identify the class label of a tuple in D. Note that the information is based only on the proportions of tuples of each class, which is also known as the entropy of D. Entropy is one of the most widespread discretization measures. It was first introduced by Shannon and Weaver (1949) in pioneering work on information theory and the concept of information gain. Entropy-based discretization is a supervised, top-down splitting technique. It explores class distribution information in its calculation and determination of split-points. To discretize a numerical attribute, A, the method takes the value of A that has the minimum entropy as a split-point, and recursively partitions the resulting intervals to reach a hierarchical discretization. Such discretization generates a concept hierarchy for attribute A.

Let now us partition the tuples in D on some attribute A having v distinct values, $\{a_1, a_2, \ldots, a_V\}$, as observed from the training data. If A is discrete-valued, these values correspond directly to the v outcomes of a test on A. Attribute A can be used to split D into v partitions, $\{D_1, D_2, \ldots, D_V\}$, where D_j contains those tuples in D that have outcome a_j of A. These partitions would correspond to the branches grown from node N. Let this partitioning produce an exact classification of the tuples. However, it is quite likely that the partitions will be impure. To find an exact classification, the amount of information is calculated by

$$Info_A(D) = \sum_{j=1}^{v} \frac{|D_j|}{|D|} x Info(D_j) \qquad (2)$$

The term $\frac{|D_j|}{|D|}$ acts as the weight of the jth partition. $Info_A(D)$ is the expected information to classify a tuple from D based on the partitioning by A. The smaller the expected information required, the greater the purity of the partitions. Information gain is given by:

$$Gain(A) = Info(D) - Info_A(D) \qquad (3)$$

The attribute A with the highest information gain, $Gain(A)$, is chosen as the splitting attribute at node N. Readers interested in further details on the entropy technique for the details are referred to Han and Kamber (2006).

In this approach, in order to determine fall risk, an algorithm has been determined by classifying the biomechanical parameters in terms of the produced decision tree. Since some of the biomechanical parameters contain quantitative values, the algorithm C4.5 has been preferred. Medians of the biomechanical parameters which consist of the quantitative values have been calculated. Thus the biomechanical parameters are categorized in mainly two groups:

i) the values of the biomechanical parameters are less than or equal to median,

ii) the values of the biomechanical parameters are greater than median. When considering the biomechanical parameters: lumbar strain, pectoral strain, hamstring strain and gastro-soleus strain; the previous first and second groups are considered to be not-strained and strained, respectively. For fall risk, the classes are $C_{low}=3$, $C_{medium}=3$, $C_{high}=3$ and $C_{very high}=15$. In this respect, the probabilities are found to be $P_{low}=\frac{3}{24}$, $P_{medium}=\frac{3}{24}$, $P_{high}=\frac{3}{24}$ and $P_{very\ high}=\frac{15}{24}$. The entropy values in the sense of the average amount of information can be easily found using Equation (1). Using Equation (2), the entropy values in the sense of expected information have been calculated for each value of the biomechanical parameters. Also, using Equation (3), the information gain for the biomechanical variables can be seen in Table 1. As can be seen from Figure 1, the trunk lateral flexion has been seen to be root of decision tree and it has the maximum value of the information gain.

As can be seen from Figure 1, the dominant leg eyes open and non-dominant leg eyes open has been seen to be the left branch of the decision tree and it has the maximum value of the information gain.

The fall risk is classified for the case of “less or equal to” of the trunk lateral flexion, and using Equation (1) the entropies of the trunk lateral flexion were calculated. For the case of “less or equal to” of the trunk lateral flexion, using Equation (2), the entropy values in the sense of expected information have been calculated for each value of the biomechanical variables. For the same case, also, using Equation (3), the information gain for the biomechanical parameters can be seen in Table 2. As can be seen from Figure 1, the dominant leg eyes open and non-dominant leg eyes open has been seen to be the left branch of the decision tree and it has the maximum value of the information gain. As can be clearly seen from Figure 1, the fall risk is classified for the case of “less or equal to” of the dominant leg eyes open and non-dominant leg eyes open, and has been found to be “very high”. On the other hand, there exist two different cases for the case “greater” of the parameters of the dominant leg eyes open and non-dominant leg eyes open, and as is the case before, the entropy values and information gain have been calculated for the cases “greater” of the two parameters. The information gains of the biomechanical parameters are equal for the case of “dominant leg eyes open-greater”. Similarly, the information gains of the biomechanical parameters are equal for the case of “non-dominant leg eyes open-greater”. The corresponding decision trees are seen in Figure 1.

Table 1. The computed information gains of the biomechanical variables

Biomechanical parameters	**Gain**	**Biomechanical parameters**	**Gain**
Trunk lateral flexion	0.5826	Elbow flexion	0.1821
Dominant leg eyes open	0.5488	Hip abduction	0.1821
Non-dominant leg eyes open	0.5488	Fifth metatars dominant leg	0.1805
Dominant leg eyes closed	0.4856	Shoulder external rotation	0.1643
Non- Dominant leg eyes closed	0.4855	Knee flexion	0.1643
Trunk hyper extension	0.4211	Hip flexors strain	0.1643
Age	0.4138	First metatars of dominant leg	0.1635
Functional reach	0.3623	Shoulder flexion	0.1493
Second metatars of dominant leg	0.3475	Dominat lateral foot CPT	0.1425
Shoulder abduction	0.3437	Hamstrings strain	0.1274
Second metatars of non-dominant leg	0.3063	First metatars of non-dominant leg	0.1274
Pectoral strains	0.3053	Smoking	0.1218
Fourth metatars of non-dominant leg	0.2583	Fourth metatars of dominant leg	0.1148
Hip external rotation	0.2479	Shoulder internal rotation	0.0924
Hip flexion	0.2478	Dominant legs heel	0.0819
Fifth metatars non-dominant leg	0.2421	Supination	0.0706
Third metatars of non-dominant leg	0.2167	Pronation	0.0706
Gastro-soleus strains	0.2166	Non-dominat lateral foot CPT	0.0616
Hip internal rotation	0.2044	TFL strains	0.0598
Dorsi flexion	0.2044	Third metatars of dominant leg	0.0362

Lumbar strains	0.2044	Non-dominant legs heel	0.0125
Plantar flexion	0.1967	Sex	0

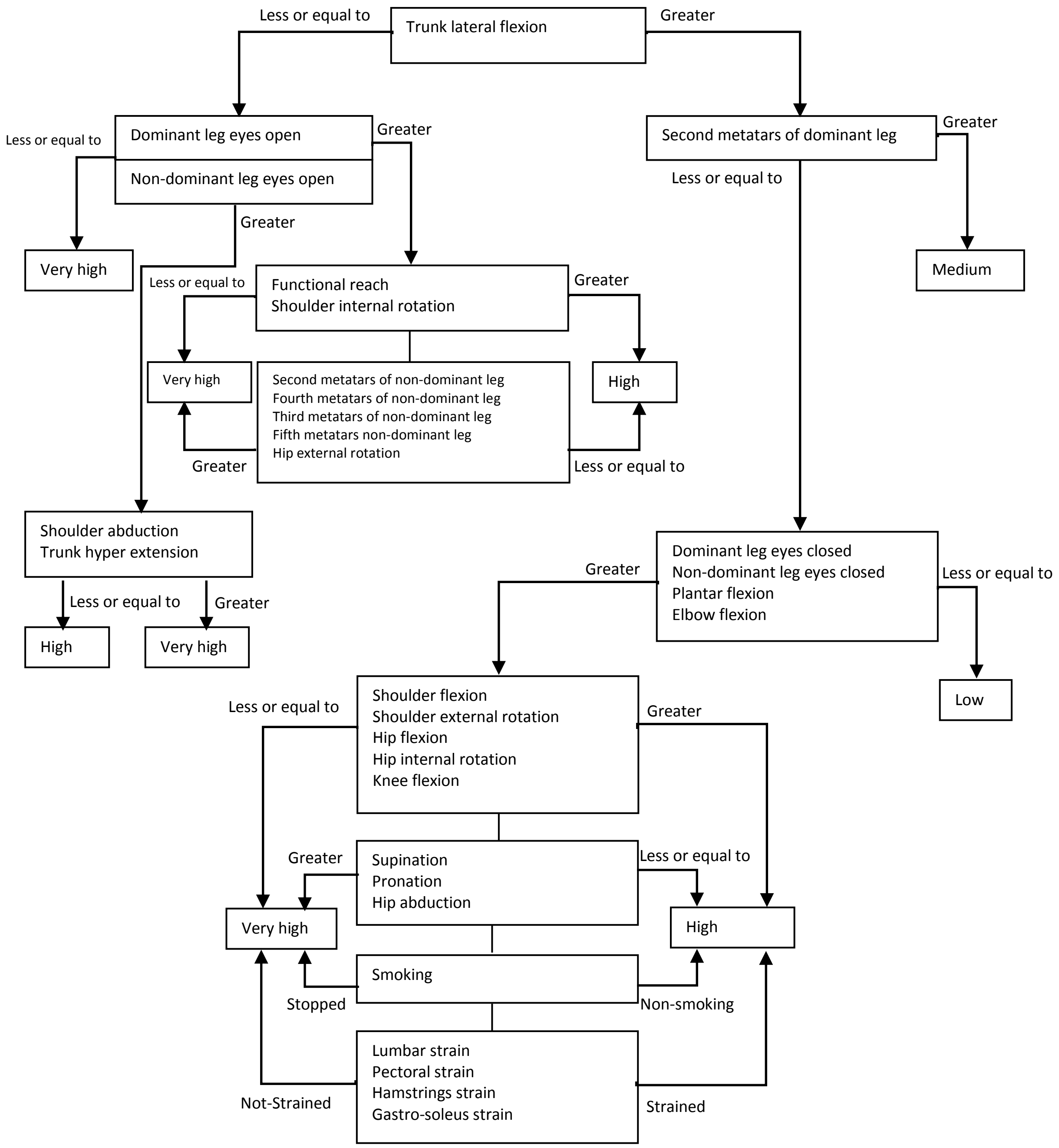

Figure 1. The decision tree

The fall risk is classified for the case of "greater" of the trunk lateral flexion, and using Equation (1) the entropies of the trunk lateral flexion were calculated. For the case of "greater" of the trunk lateral flexion, using Equation (2), the entropy values in the sense of expected information have been computed for each one of the biomechanical variables. For the same case, also, using Equation (3), the information gains of the biomechanical parameters have been presented in Table 3. As can be seen in Figure 1, the second metatars of dominant leg has been seen to be right branch of the decision tree and it has the maximum value of the information gain. As seen from Figure 1, the fall risk is classified for the case "greater" of the second metatars of dominant leg, and has been found to be "medium". Also, the information gains of the biomechanical parameters (dominant leg eyes closed, non-dominant leg eyes closed, plantar flexion and elbow flexion) have been found to be maximum for the case "less or equal to" of the second metatars of dominant leg. The corresponding decision trees are given in Figure 1. For the case "less or equal to", the fall risk has been found to be "low" for the case of the biomechanical parameters (dominant leg eyes closed, non-dominant leg eyes closed, plantar flexion, elbow flexion). When taking the case "greater", as presented in Figure 1, the biomechanical variables (shoulder flexion, shoulder external rotation, hip flexion, hip internal rotation, knee flexion, supination, pronation, hip abduction, smoking, lumbar strain, pectoral strain, hamstrings strain, gastro-soleus strain) have been seen to be of equal information gains. Similar computations have been generated for the left branch of the decision tree.

Table 2. The computed information gains of the biomechanical variables for the cases "Greater" in trunk lateral flexion

Biomechanical parameters	**Gain**	**Biomechanical parameters**	**Gain**
Second metatars of dominant leg	0.9544	Dominat lateral foot CPT	0.4669
Dominant leg eyes closed	0.8113	Fourth metatars of dominant leg	0.4669
Non- Dominant leg eyes closed	0.8113	Fifth metatars non-dominant leg	0.4669
Age	0.8113	Hamstrings strain	0.3837
Plantar flexion	0.8113	Third metatars of dominant leg	0.3113
Elbow flexion	0.8113	Non-dominat lateral foot CPT	0.2657
Smoking	0.717	First metatars of non-dominant leg	0.1992
Trunk hyper extension	0.5436	Third metatars of non-dominant leg	0.1992
Functional reach	0.5436	Second metatars of non-dominant leg	0.1992
Shoulder abduction	0.5436	Fourth metatars of non-dominant leg	0.1992
Pectoral strains	0.5436	Fifth metatars dominant leg	0.1992
Hip flexion	0.5436	Dominant legs heel	0.1226
Gastro-soleus strains	0.5436	Non-dominant legs heel	0.1226
Hip internal rotation	0.5436	Sex	0.1225
Lumbar strains	0.5436	Hip flexors strain	0
Shoulder flexion	0.5436	Dorsi flexion	0
Pronation	0.5436	Hip external rotation	0
Hip abduction	0.5436	TFL strains	0
Supination	0.5436	Dominant leg eyes open	0
Shoulder external rotation	0.5436	Non-dominant leg eyes open	0
Knee flexion	0.5436	Shoulder internal rotation	0
First metatars of dominant leg	0.4669		

The fall risks of those biomechanical parameters have been indicated in Figure 1. To determine the effects of the biomechanical variables, programming codes have been produced using the decision tree. The produced codes in C# are as follows:

…

If "Trunk lateral flexion" is "Greater"**and**"Second metatars of dominant leg"is "Greater" **than** "Fall risk" is "**Medium**"

If "Trunk lateral flexion" is "Less or equal to"**and** "Dominant leg eyes open"is "Less or equal to" **or**""Non-dominant leg eyes open" is "Less or equal to " **than** "Fall risk" is "**Very High**"

…

Table 3. The computed information gains of the biomechanical variables for the case "Less or Equal to" in trunk lateral flexion

Biomechanical parameters	**Gain**	**Biomechanical parameters**	**Gain**
Dominant leg eyes open	0.2936	Elbow flexion	0
Non-dominant leg eyes open	0.2936	Hip abduction	0
Shoulder abduction	0.138	Fifth metatars dominant leg	0
Smoking	0.0609	Shoulder external rotation	0
Age	0.0257	Knee flexion	0
Shoulder internal rotation	0.0561	Hip flexors strain	0
Shoulder flexion	0.0065	First metatars of dominant leg	0
Sex	0.0060	Non- Dominant leg eyes closed	0
Functional reach	0	Dominat lateral foot CPT	0
Second metatars of dominant leg	0	Hamstrings strain	0
Second metatars of non-dominant leg	0	First metatars of non-dominant leg	0
Pectoral strains	0	Dominant leg eyes closed	0
Fourth metatars of non-dominant leg	0	Fourth metatars of dominant leg	0
Hip external rotation	0	Trunk hyper extension	0
Hip flexion	0	Dominant legs heel	0
Fifth metatars non-dominant leg	0	Supination	0
Third metatars of non-dominant leg	0	Pronation	0
Gastro-soleus strains	0	Non-dominat lateral foot CPT	0
Hip internal rotation	0	TFL strains	0

Dorsi flexion	0	Third metatars of dominant leg	0
Lumbar strains	0	Non-dominant legs heel	0
Plantar flexion	0		

to evaluate the effects of the input variables, the codes have been produced using the decision tree. The developed program has been tested for 24 subjects.

3. Results

Twenty-four subjects were included in this study. In the current study, measurements were done by using the aforementioned methods. The entropies and their information gains were calculated in terms of the obtained results. Then the decision tree was prepared by using the information gains. The computer codes in C# programming language were produced considering the decision tree. The program codes were applied for the twenty-four subjects. The computed results and examination results of physiotherapist were seen to be in very good agreement as seen in Table 4 (92%). By using the chi-square analysis, it is found a statistically significant relation between the computed results and the physical examination results (X^2 =21.95 for Fisher's Exact, $p<0.001$, Pearson's R=0.977 and kappa=0.852). The slight difference may stem from either/both the lack of measurements of the physiotherapist or/and the computed results. As realized from Figure 1 and Table 1, it was found that the most important one is trunk lateral flexion parameter among 46 parameters of interest. For fall risk, the other important parameters are "non-dominant/dominant leg eyes open" and "second metatars of dominant leg eyes open" in standing test (see Figure 1 and Tables 2-3). Level of importance of other fall risk parameters can be seen from the decision tree given in Figure 1.

4. Discussions

In the work of Bongue *et al.* (2011), falls were tried to be predicted by a screening tool with only five risk factors (gender, living alone, psychoactive drug use, osteoarthritis, and previous falls) and one clinical test. Rueangsirarak *et. al.* (2012) has also used the screening tool to predict fall risk. In another work, Keskin et al. (2) found that knee extensor and flexor strength have no significant effect on fall risk in elderly women who are able to function independently. They also found that age, smoking, body mass index, the number of medications taken and comorbid disease are not related to falling. Standing tests were seen not to be effective predictors of falls in older adults. However, the produced result by using the developed method here showed that standing tests are seen to be effective for fall risk. Since the increase of number of physical parameters is more realistic, it is believed that, the number of parameters used in determination of fall risk may cause this contradictory (our study: 46 parameters, theirs: 5 parameters). Lajoie *et al.* (2002) reported that reaction time could be an interesting predictor of falls in the elderly, due to the sensory and motor components associate with it. To the best of the authors' knowledge, fall risks were analyzed for mostly elderly people in the literature while the current research was carried out not for only elderly but also non-elderly people. The relation between balance and fall risk was studied in the literature (Cimbiz and 2005, Ghanavati *et al* 2012). Our study and most literature are seen to be in agreement.

Table 4. Comparison of the computed and physical examination results for fall risk

		Computed Results				
		Very High	High	Medium	Low	Total
Physical Examination Results	Very High	15	-	-	-	15
	High	-	3	-	-	3
	Medium	-	-	1	-	1
	Low	-	-	2	3	5
	Total	15	3	3	3	24

As a conclusion, before recommending this tool for widespread clinical/nonclinical use, it should be tested in a wider population with at least more different characteristics from those of the development sample. This is a pilot and guiding study for researchers. For a widespread and well-organized future study, attention may be paid on a considerable and collaborative project considering cultural differences, life standards and habitat.

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