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Identification of Risk Factors for Scoliosis in Elementary School Children Using Machine Learning

Ahmad Aizat Che Rahmat[1], Siti Zura A. Jalil[2]*, Sharifah Alwiah Syed Abd Rahman[2], Sahnius Usman[2], Mohammad Shabbir Alam[3]

[1]Temerloh District Health Office Temerloh,
Ministry of Health Malaysia, Pahang, 28000, MALAYSIA

[2]Razak Faculty of Technology and Informatics,
University Teknologi Malaysia, Kuala Lumpur, 54100, MALAYSIA

[3]College of Computer and Information Technology,
Jazan University, Jizan Kingdom of SAUDI ARABIA

*Corresponding Author

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Abstract: Scoliosis is an abnormal curvature of the spine and often diagnosed in childhood or early adolescence. In this study, the risk factors for scoliosis in elementary school children is investigate based on age, backpack weight and gender. There are 260 children participated in this study from aged 7 up to 12 years old. Scoliometer is used to measure the angle of trunk rotation (ATR) on Adam Forward Bending Test. Statistical analysis of analysis of variance (ANOVA) is used to determine the characteristic difference of ATR readings on the risk factors for scoliosis. Significant results with P-value less than 0.001 are found among ATR readings on a linear combination of risk factors for scoliosis of age and backpack weight. Then, the risk factors for scoliosis are classified among elementary school children using Decision Tree and K-Nearest Neighbor. The classification results shown that both Decision Tree method produced highest classification percentage up to 98.08%. This finding indicates that age and backpack weight are significant as the risk factors for scoliosis.

Keywords: Backpack weight, angle of trunk rotation, scoliosis, elementary school, decision tree, KNN

1. Introduction

In recent years, studies have shown that carrying heavy school bags has been a risk factor for musculoskeletal disorders [1, 2]. Besides carrying the books, students also carry other items that can contribute to the weight of the bag. There are several types of school bag used by students. Most common types are backpack, shoulder bag and wheel bag. As they create a symmetrical postural variance in one body in response to load, wheel bag may be more appropriate for load carriage within the young student population [3]. In both, the shoulder and wheel bag create postural deviations that can inflict adverse stress and stress on spinal structures and eventually lead to discomfort and incremental postural scoliosis [4]. In addition, studies show that prolonged use of a backpacks can cause variations in the body's physiological and muscular activity between the right and left side. [5].

Studies shows different factors that affect the healthy use of schoolbags for children [6]. These included an emphasis on the characteristics of the bag, such as the size of the bag and bag design [7]. Recent concern for children and teenager are the condition of the spine and scoliosis. During the early stages of the school, the body is relatively stable. Scoliosis

*Corresponding author: sitizura.kl@utm.my

and kyphotic diseases dominate within six to seven years, as when the children start schooling and carrying heavy backpack is part of their daily routine [8 - 10]. If it persists, it can interfere with one's posturogenesis [11]. Therefore, state of unstable posture has occurred to children nowadays may due to a heavy backpack. It is shows that this problem had occurred between 40% to 70% among children in developed countries [11, 12]. Studies suggest the maximum recommended load for children is 10% of their weight [13, 14].

The discomfort arises while carrying heavy loads is called "backpack bag syndrome," according to the report by Chow et al [15]. This condition brings with different problems such as spinal pain, dizziness, exhaustion. If this condition lasts for a long time, it can contribute to scoliosis. The biomechanics, physiology and physics of the child also have an effect on children who carry excessive weight for backpacks. As a result, the posture of the child will shift, particularly the child's spine. Scoliosis may occur if this condition continues [6]. The result consequences of carrying heavy school bag on the studied child is include pain or discomfort, altered gait patterns, postural misalignment and other physiological issues [16-19].

Scoliosis is an abnormal curvature of the spine and shows in an “S” or “C” shape. In general, scoliosis is confirmed through physical examination, an x-ray, spinal radiograph, CT scan and magnetic resonance imaging (MRI). The curve is measured by the Cobb Method and the main diagnostic criteria are the angle of the curve measures more than 10 degrees on an anteroposterior X-ray image. In the United States, the most widely used screening test for scoliosis is the Forward Bend Test [20]. It is a non-invasive screening technique in which, the spine is parallel to the horizontal plane, a person bends forward at the waist at 90º angle and the examiner tests for spinal asymmetry on the back. If the patient’s back is completely straight, no scoliosis is found. But if the patient’s back has a prominent line where the spine is and one side is higher than the other, scoliosis is shown. Forward Bend Test also known as Adam’s forward bend test. It was found by William Adams in 1865.

Adam’s forward bend test can be used with and without a scoliometer. Most school-based scoliosis screening services used Adam’s forward bend test to check for scoliosis [21-22]. Adam’s forward bend test and a scoliometer are very well known and commonly used instruments for physical examinations in diagnosis of back symmetry and the presence of scoliosis [23-24]. A scoliometer is a tool to measure trunk asymmetry. When combined with Adam’s forward bend test, the scoliometer can lead to early detection of scoliosis. It can help detect signs of scoliosis, measure the angle of rotation of the trunk and divulge the need for further testing. Thus, will increases the success of the treatment. Besides, the scoliometer also a non-invasive measurement, free from radiation exposure, and a relatively inexpensive screening method compared to other techniques as mention above. It also easy to use and has been found to have strong correlation analysis and excellent intra-rated reliability [25].

Interest in pattern recognition studies of adolescent idiopathic scoliosis classification has received much attention in recent years [26, 27]. Decision tree and K-Nearest Neighbor (KNN) were used for the purpose of classification and had shown significant finding. However, most studies have been focused based on image processing techniques [28, 29]. Thus, there are still opportunities to classify the risk factors for scoliosis based on ATR measurement.

Children carrying excessive school bags in elementary schools in Malaysia has growing concern. The complications of scoliosis have shown increases when the children carrying excessive bags incorrectly for a long period of time [10, 30]. Previous study shows that the relationship between backpack weight and scoliosis among students in elementary school was significant [31]. Therefore, in this study, the risk factors for scoliosis will be further identified.

2. Methodology

In this study, the methodology is comprised of four parts. The first part is data collection of ATR reading on elementary school pupils. Next, the tools for measurement process is discussed on second part. Then, the third part is comparing the means of the risk factors for scoliosis using statistical test and finally, machine learning techniques of decision tree and KNN is employed to identify significant risk factors.

2.1 Data Collection

Data collection which involves Angel Trunk Rotation (ATR) reading and related risk factor used in this study. The risk factors of age, gender and backpack weight are carried out at the Elementary School located in Pahang, Malaysia. During the measurement process, a doctor, nurse, physiotherapy, and three assistants are involved to assist in data recording. There are 260 school children participated in this study. All samples are randomly selected, from aged 7 up to 12 years old and from Elementary 1 to Elementary 6. The pupil’s BMI is determined by measuring pupil’s height and weight, while the backpack weight is determined by taken the mean value of the backpack weight that recorded in three consecutive days.

2.2 Tools

The positive curve of the spine is measured using scoliometer and Adam Forward Bending Test. The ATR is the calculation of trunk rotation by a scoliometer. The Scoliosis Research Society recommends an ATR of 5° to 7° as a referral threshold for radiography [32, 33]. If the ATR reading is equal to or greater than 5°, it specifies there is a risk factor for scoliosis [34]. The Gold Standard test for diagnosing scoliosis is to use MRI. Meanwhile, X-rays image and

CT scan of the spine is performed to monitor the curve progress and vertebral anomalies [35]. Fig. 1 shows the measurement process using scoliometer. An example of x-ray test for scoliosis is shown in Fig.2

Fig. 1 - Measurement process using Scoliometer

Fig. 2 - X-ray test for scoliosis

2.3 Statistical Analysis

In previous studies, a correlation analysis was performed using Pearson product-moment correlation coefficient. In this study, the analysis of variance (ANOVA) is employed to compare the mean and to determine the characteristic difference of ATR readings on the risk factors for scoliosis. ANOVA has been previously shown to be capable to compare group for differences [36]. It is used to establish significant differences among linear combination of variables.

2.4 Classification

For the purpose of classification, two techniques of classification known as Decision tree and K-Nearest Neighbor (KNN) are used. Both decision tree and KNN are nonparametric supervised learning technique. The input features for all classifiers are designed using significant variables resulting from statistical analysis. The classification results from these classifiers are then compared to decide a better classification method. The performances of classification for each model are determined based on the accuracy and ROC analysis in sensitivity and specificity.

The decision tree learning algorithm uses a tree-like (top-down) model to generate a decision. Each node represents a feature (attribute), each branch represents a decision (rule) and each leaf represents a classification outcome or decision. The top-most decision node in a tree is root node, which corresponds to the best predictor. Fig. 3 shows an illustration of decision tree process. The root node is split into a number of branches and leaf node. The process that dividing a node into two or more sub-nodes is called as splitting. Sub-nodes that splits into further sub-nodes is known as decision node, while leaf node is the node that do not split to another node.

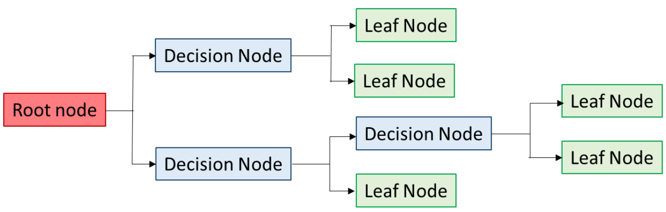

Fig. 3 - Decision tree process

Decision tree J48 is also known as C4.5 algorithms in WEKA is the successor of algorithm ID3 (Iterative Dichotomiser 3) [37]. All of them used a greedy and a top-down approach to find a good attribute to split on at each stage in decision tree making. Information Gain is used to choose the attribute at each stage and to decide the splitting points, while entropy of information is used to measure the homogeneity of a sample. Entropy is the measure of uncertainty or impurity in the dataset. A branch with an entropy zero is leaf node, while a branch with entropy more than zero need further splitting. Mathematically for one attribute it can be calculated for any values of k as follows,

$$E(S) = -\sum_{i=1}^{k} p_i \log_2 p_i \quad (1)$$

where S is the current state and p_i is the probability of getting the ith value when randomly selecting of state S. For multiple attributes, entropy can be calculated as,

$$E(T,X) = \sum_{k \in X} P(k)E(k) \quad (2)$$

where T is the current state and X is selected attribute.

Information gain is a statistical property that measures how well a given attribute separates the training examples according to their target classification. It is used to decide ordering of attributes in the nodes of a decision tree. Information gain is calculated as follows,

$$\text{Information Gain (T,X)} = \text{Entropy (T)} - \text{Entropy (T,X)} \quad (3)$$

Information gain is a decrease in entropy. Decision tree is constructed by finding an attribute that having highest information gain and the smallest entropy.

Meanwhile, KNN algorithm is a most used and one of the simplest technique in machine learning that commonly used as a classification algorithm instead of regression. It is a type of lazy learning algorithm because it does not learn from the training set immediately. It just stores the dataset during the training phase and the computation will happen when a classification is being made. Since it relies deeply on memory to store all of its training data, it is also referred to as memory-based learning methods.

In KNN, the data points are separated into several classes to predict the classification of a new sample point. It uses proximity to make classifications or predictions about the grouping of an individual data point, with the assumption that similar points can be found near one another. It classifies that data into a category that is much similar to the new data. Fig. 4 shows the illustration of KNN algorithm. The new data will lie in category A or category B.

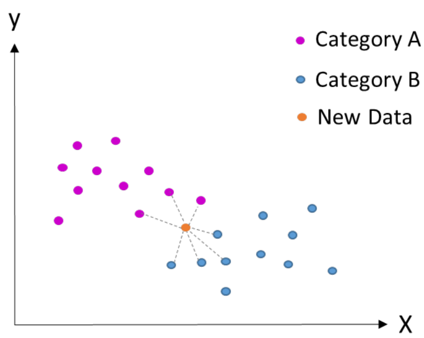

Fig. 4 - KNN algorithm

When new or unknown data is found, the KNN classifier finds the most similar k to the closest neighborhood of the training sample and allocates x to the class that seen most frequently in the neighborhood. KNN determines the labels of the new or unknown data using the k nearest neighbors. Euclidean distance is used as a distance metric criterion to find the nearest distance and to determine which data are in the neighborhood. Euclidean distance offers a good choice for such a distance function if the data is numerical and has been used in many applications [38, 39]. If the new or unknown data point has attribute values s_1 to s_r, the distance $d(s, x_j)$ between point s to any data point x_j can be calculated by

$$d(s, x_j) = \sqrt{(s_1 - x_{j1})^2 + \cdots + (s_r - x_{jr})^2} \quad (4)$$

2.5 Experimental Design

Prior the classification, statistical analysis is performed to determine significant input variables for classification. Statistical analysis of ANOVA is implemented using Minitab version 21 to determine the characteristic difference of ATR readings on the risk factors for scoliosis.

In this study, both Decision tree and KNN classifications are performed using WEKA version 3.8.3. WEKA is Waikato Environment for Knowledge Analysis (WEKA) was developed at the University of Waikato, New Zealand. WEKA is a free licensed software under GNU General Public License. The input features used for classification are refers to the significant finding in the statistical analysis of ANOVA. The output feature is ATR readings. The risk factor for scoliosis is determine if the ATR reading is equal to or greater than 5° [34]. Thus, in this analysis there are two class of ATR reading is used for classification, that is ATR readings of ≥ 5° (having risk) and ATR readings of < 5° (no risk).

In both classifications using Decision tree and KNN, at first, the risk factors of scoliosis are classified using holdout technique, in which the test data is randomly selected for approximately 20% of the complete data set. The training and testing sets ratio is evaluated at 80 to 20. A method of data randomization is also employed for the classification to attain the best performance. Then, the risk factors of scoliosis are classified using k-fold cross-validation technique to validate the finding with k=10.

2.6 ROC Analysis

Receiving operating characteristic (ROC) analysis is often used as a tool to evaluate the performance of binary classification algorithms. It is used to draw an unknown conclusion, where as a test to separate the population into two possible outcomes that are positive or negative. In ROC analysis, all performance measures are obtained based on four possible outcomes called true positive (TP), false positive (FP), true negatives (TN) and false negatives (FN). TP exhibits the correct classification of positive cases i.e. it is positive and is classified as positive, while TN exhibits correct negative case classification i.e. it is negative and it is classified as negative. On the other hand, FP exhibits the classification of false positive cases if it is positive but it is counted as negative, while FN exhibits incorrect negative case classification i.e. it is negative but it counts as positive.

The important measures of classification accuracy are sensitivity and specificity. Sensitivity and specificity has been used broadly in diagnostic of medical applications as the classification performance measures [40, 41]. Sensitivity quantifies the proportion of true positives that are correctly identified, while specificity quantifies the proportion of negatives that are correctly identified. Sensitivity and specificity are computed as follows,

$$sensitivity = \frac{TP}{TP+FN} = \frac{TP}{P} \tag{5}$$

$$specificity = \frac{TN}{TN+FP} = \frac{TN}{N} \tag{6}$$

The accuracy of the classification is estimated in terms of the probability of specificity and sensitivity, which is calculated as,

$$accuracy = \frac{TP+TN}{P+N} \tag{7}$$

3. Results and Discussion

There are 260 pupils (130 males and 130 females) were participating in this study. All the participants were randomly selected. Scoliometer was used to measure the Angel Trunk Rotation (ATR) on the Adam Forward Bending Test. The body mass index and backpack weight were measured among age and gender. Table 1 shows the mean and standard deviation value for the risk factors involved for both male and female [31]. The mean for mass is 33.63 kg, therefore the maximum allowable load recommended for these pupils is 3.36 kg which is about 10% of the pupil's weight [13]. However, it found that the mean for the backpack weight carried by pupil is 5.24 kg, which higher than maximum allowable weight for this group of pupils. The finding also shows that more than 50% of both male and female pupils having ATR reading at 5° and above (Table 2), which is considered having risk factors for scoliosis [34].

Table 1 - Mean and standard deviation

	Mean	Std.Deviation
Age	9.48	1.72
Height (cm)	133.65	11.55
Mass (kg)	33.63	13.82
Backpack Weight (kg)	5.24	1.47
ATR Reading	4.52	2.42

Table 2 - ATR readings between genders [31]

Gender	ATR Reading	Number of pupils
Male	< 5°	53
	≥ 5°	77
Female	< 5°	46
	≥ 5°	84

3.1 Statistical Analysis

In previous analysis, a Pearson product-moment correlation analysis was used to determine the strength of ATR reading between risk factor of scoliosis and found that a positive and medium correlation between gender, age, backpack weight and with ATR reading [31]. Therefore, in this analysis, the analysis of variance (ANOVA) is used to further investigated the risk factors of scoliosis of gender, age and backpack weight on ATR reading. The results of ANOVA indicate there is statistically significant differences among ATR readings on a linear combination of risk factors of age and backpack weight which obtained the significant value of $\rho < 0.001$. The computed value of the test statistic for age is $f_0 = 35.47$ and for backpack weight the $f_0 = 9.49$. Since both having the P-value is less than 0.001, therefore it is confirmed the difference among group of ATR readings of ≥ 5° and ATR readings of < 5° in age and backpack weight. Nevertheless, the risk factor of gender is found not significant in this analysis as the P-value is more than 0.05.

3.2 Classification

For the purpose of classification, two classification techniques of Decision tree and K-Nearest Neighbor (KNN) are used. In both classifiers, the risk factors of scoliosis are classified using holdout technique with the training and testing sets ratio is evaluated at 80 to 20, and 10-fold cross-validation technique.

The input features used for classification are refers to the significant finding in the statistical analysis of ANOVA. Two risk factors of scoliosis used are age and backpack weight. From the simulation, the results for the classification of both classifiers using two techniques of classification are shown in Fig. 5. For holdout technique, both classifiers produce similar classification accuracy of 98.08%. For 10-fold cross validation, the highest classification accuracy is 97.69% using KNN, while decision tree produces the classification accuracy of 96.15 %. Different classification accuracy produced between holdout technique and 10-fold cross-validation is due to total number of instances used in data splitting between training and testing. In holdout technique, only 52 data used for testing (20%), while 260 data are used in 10-fold cross-validation technique. In overall, both classifier of KNN and decision tree produced highest classification percentage more than 95%. The finding confirms that age and backpack weight are significant as the risk factor for scoliosis.

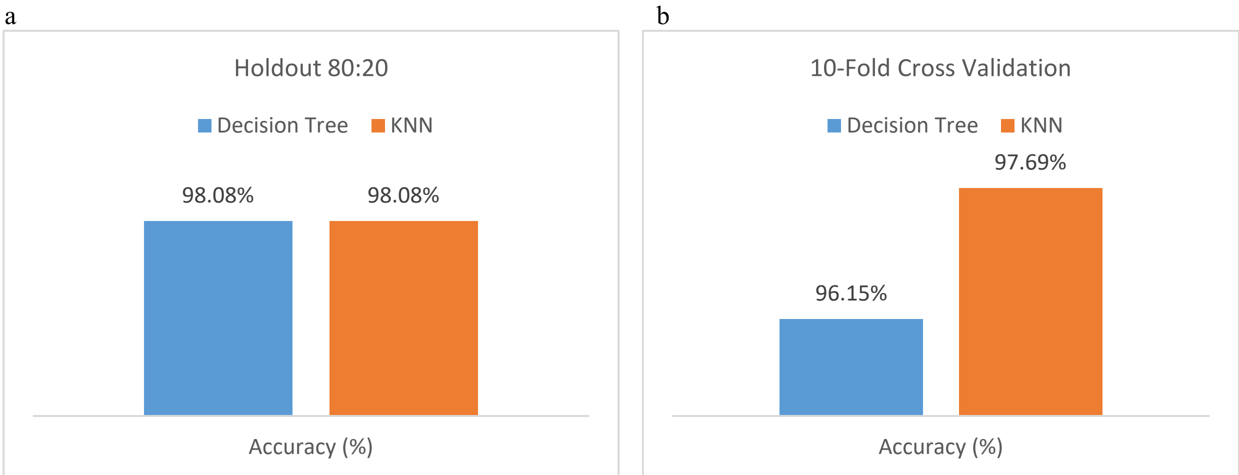

Fig. 5 - Classification accuracy (a) holdout (b) cross-validation

The performance of the classifiers in recognizing the risk factors of scoliosis is carried out by defining and comparing the sensitivity and specificity of each classifier. Sensitivity and specificity has been used broadly in diagnostic of medical applications as the classification performance measures [40, 41]. The sensitivity and specificity computed for each of the risk factors for all classifiers are shown in Table 3. Sensitivity measures the proportion of ATR readings of ≥ 5° which are correctly identified, whilst specificity measures the proportion of ATR readings of < 5° which are correctly identified.

All classifiers are found having higher specificity, indicating that the classifier is able to distinguish ATR readings of ≥ 5° better than ATR readings of < 5°. However, since most of the ATR readings are found to have the highest sensitivity and specificity up to 100%, this specifies that the classifiers are ideal for classifying the risk factors of scoliosis and are able to correctly classify the ATR readings.

Table 3 - Sensitivity and specificity

Test Mode	Holdout 80:20		10-fold Cross Validation	
Classifier Technique	Decision Tree	KNN	Decision Tree	KNN
Sensitivity	95.8%	95.8%	94.3%	97.5%
Specificity	100%	100%	97.8%	97.7%

Further analysis also has been conducted to prevent the chance of overfitting in the model by comparing the accuracy of training and testing set of data. Table 4 and Table 5 demonstrates the confusion matrix table and percentage of sensitivity and specificity in training and testing, respectively for 10-fold cross validation using decision tree. The analysis shows that not much difference between training and testing accuracy and it is common for training accuracy is slightly higher than testing accuracy. This is due to training accuracy is referred to identical instances are used both for training and testing, while test accuracy represents that the trained model identifies independent instances that were not used in training. The ROC curve for this analysis is shown in Fig. 6. The ROC curve or area under the curve (AUC) measure of the ability of a classifier to distinguish between classes of ATR readings of ≥ 5° and ATR readings of < 5° and provides a better measure than accuracy. It is found that the AUC for both training and testing are more than 0.9 suggests an outstanding performance in distinguishing between classes of ATR readings of ≥ 5° and ATR readings of < 5°.

Table 4 - Confusion matrix table

	Predicted Class	
Actual Class	Training (% Correct)	Testing (% Correct)
≥ 5°	99.2	94.3
< 5°	97.8	96.4

Table 5 - Sensitivity and specificity in training and testing

	Training (%)	Testing (%)
Sensitivity	99.2	94.3
Specificity	97.8	96.4

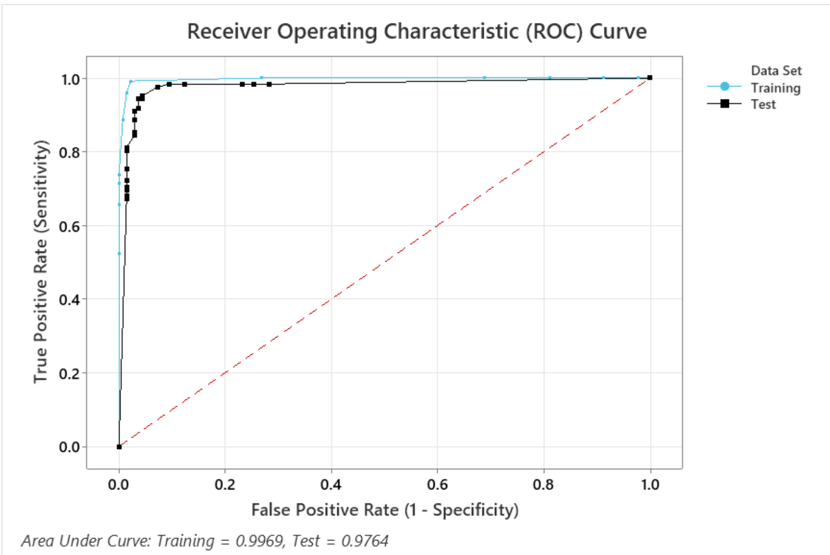

Fig. 6 - ROC curve for 10-fold cross validation using decision tree

This finding indicates the necessities of physical examination to diagnose the back asymmetry of elementary school children. Backpack weight has shown significant for this age group of growth. In the further, optimal backpack weight need to be investigated with careful consideration on several factors. This include the load to be carried on a daily basis, the style of children carrying backpacks and the duration of the carrying excessive backpacks weight. Children carrying excessive weight over their strength, may cause bend on their head and body forward to hold the excessive weight and will use the muscle strength to maintain the balance of body. The neck and the back muscle also will stress due to excessive fatigue and may damage the skeletal system. Monitoring the weight of children's backpacks by parents and teachers, as well as the children themselves, by encouraging them to leave books at school will certainly help in minimizing the daily stress on the children's spine [10].

4. Conclusion

This study is aims to identify the risk factors for scoliosis in elementary school children. 260 pupils from aged 7 up to 12 years old were randomly selected to participate in this study. Scoliometer is used to gather the measured data of Angel Trunk Rotation (ATR) on the Adam Forward Bending Test. The risk factors used were age, gender and backpack weight. In ANOVA analysis, the significant value of $\rho < 0.001$ that indicates there is statistically significant differences among ATR readings on a linear combination of risk factors for scoliosis of age and backpack weight. Then, two classification techniques of Decision tree and K-Nearest Neighbor (KNN) were used to classify the risk factors for scoliosis among elementary school children using holdout technique with the training and testing sets ratio at 80 to 20, and 10-fold cross-validation technique. The classification results shown that all methods produced highest classification percentage up to 98.08%. The finding confirms that age and backpack weight are significant as the risk factor for scoliosis. In the future, the study will investigate the effect of type of backpacks, duration of carrying a backpack, and the style of pupils carrying the backpack on the risk factors for scoliosis.

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