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Research Article

An Automatic Labeling Approach Towards Multi-class Sitting Posture Classification Based on Depth-Sensor Data

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ABSTRACT

This study aims to create a non-contact system for recognizing the sitting postures of office workers, applicable to healthy sitting monitoring. Skeletal point data were obtained via a depth sensor-based Kinect device while subjects performed five different sitting postures. Five angles have been calculated that can differentiate these postures. A fuzzy rule-based automated approach using angle values is proposed to label the data. With this method, two different data sets were created using traditional time-based labeling methods. Angular and geometric features were used to classify the depth values, and 99.6% and 98.9% accuracy were obtained with KNN and Adaboost classifiers. The proposed labeling method outperformed the traditional time-based labeling method according to the classification results. This system offers a high-performance solution for promoting healthy sitting habits in office workers and has applications in health monitoring and robot vision.

Introduction

The impact of proper sitting postures on health is gaining significance in today's modern lifestyle, where computers and technological devices are extensively used. Musculoskeletal Disorders (MSDs) are a prominent concern, with around 60% of EU workers attributing work-related health complaints to Musculoskeletal Disorders (MSDs) as their most serious problem [1]. MSDs are responsible for a substantial portion of work-related illnesses, often stemming from prolonged incorrect sitting positions. Globally, MSD cases have risen by 25% in the past decade, constituting 2% of the overall disease burden [2]. Addressing this, the study aims to enhance awareness of ergonomics and health by identifying and defining various sitting postures. The research seeks to delineate distinctions between these postures through scientific literature analysis and propose suggestions, ultimately promoting healthier habits. The potential of an automated sitting posture tracking system in fostering a healthier work environment is highlighted as a solution to mitigate health-related costs. With the data obtained from the relevant scientific literature, it is aimed to understand the differences between sitting postures and to present suggestions for this.

Related Works

Ray et al. [3] proposed an automated approach to classify construction workers' postures as ergonomic or non-ergonomic. The dataset, which contains 22226 poses compiled from twelve joint body points, has been used to classify the four postures belonging to 8 subjects. According to the experimental results, the accuracy value 94.8 has been achieved using the linear discriminant analysis (LDA) method in real time. Patsadu et al. [4] proposed a human gesture recognition system. There are six subjects, equal numbers of males and females, of various heights and weights. Two Kinect cameras have been used. They collected 7,200 and 3,600 records in the training and testing data sets, respectively. They labeled the raw data manually. They utilized BPNN (Back Propagation Neural Network) to classify three human gesture positions: standing, sitting, and laying down. They achieved the classification of three postures with 100% accuracy. Xia et al. [5] present a human action recognition system based on a Kinect device depth sensor. The dataset, which contains 6220 poses compiled from twenty body skeleton points, has been used to classify the five postures belonging to 10 subjects. They labeled the raw data using histograms of 3D joint locations.

Linear discriminant analysis (LDA) has been used for feature extraction. According to the experimental results, the accuracy value of 91.5 has been achieved using the Hidden Markov Model (HMM) to recognize five postures, including walking, sitting down, standing up, picking up, and carrying. Paliyawan et al. [6] proposed classifying office workers' sitting on the real-time skeleton data stream captured by a Kinect camera in an office work area. To create the dataset, they collected 397800 poses compiled from 10 body skeleton points belonging to 28 different subjects. The performance of several classification methods such as Decision Tree, (DT) Neural Network (NN), Naive Bayes (NB), and k-Nearest Neighbors (KNN) have been compared. They achieved the classification of one posture with 98% accuracy. Thus, real-time feedback based on the three levels of health in ergonomics has been given to subjects. Pal et al. [7] researched occupational hazards from prolonged sitting in a particular employee posture. Sitting posture recognition has been achieved using seven similarity measures. Using city-block distance, they classified two sitting body posture types with a high accuracy of 94.29% in 3.83 milliseconds. Therefore, the 6500 sitting poses containing the 16 different body skeleton points from 20 subjects have been collected to create the dataset. Yao et al. [8] proposed a new method to separate unhealthy sitting postures from others based on neck angle and torso angle detection using a Kinect sensor. While the angles have been calculated, the ten body skeleton points have been used. They collected 66330 sitting postures from 10 subjects in the five different posture classes. The method includes using a threshold at specific angle values, and they achieved 86,65 accuracy in classifying different sitting postures according to angle calculation results. There is no validation of the angle values calculated by the Kinect device in the study. Li et al. [9] proposed a method involving BPNN. The BP network used the skeleton data captured by the Kinect depth sensor to classify postures. They utilized eight skeleton points to recognize the sitting posture of 100 subjects. While they recognized four types of body posture, they achieved 97.77 accuracy for sitting posture. Bei et al. [10] present a sitting posture classification method based on a Kinect device depth sensor. The dataset, which contains 16200 poses compiled from six body skeleton points, has been used to classify the nine postures belonging to 18 subjects. According to the experimental results, the accuracy value of 95.8 has been achieved using the fusion of the body skeleton point features and the KNN method.

Research Gap

The existing literature does not clearly explain how various sitting postures are identified or the medical studies and standards underpinning them. This study examined relevant medical and health literature to precisely define the standard sitting posture, incorporating specific expressions and angle values to address this gap. In addition to establishing four distinct sitting postures to differentiate the standard from others, this research also revealed disparities between the subjects' preferred comfortable and standard sitting postures through classification.

Some studies have relied on observational methods to categorize body postures. In contrast, this study introduces a Kinect-based angular features method to address the limitations associated with qualitative observations. Many studies in the literature have proposed a single method for data classification, which may hinder the generalizability of findings. To overcome this limitation, this study classified five different sitting postures using angular features obtained from the Kinect device with eight classifiers. The classification results were then compared with existing studies in the literature. The comparison indicated that higher accuracy values were achieved with fewer joint points.

Material and Method

Determination of Sitting Postures

The suggestions of the studies in the literature [11]–[15] and definitions in ISO 7250-1:2017 [16] have been referred to for the determination of sitting postures. One is a healthy and standard body posture defined according to suggestions in the literature and ISO 7250-1 standard. A sample drawing of a healthy and standard body posture determined according to these suggestions in [11], [15], [16] is given in Figure 1 [12]. The five different positions that were determined are given in Table 1.

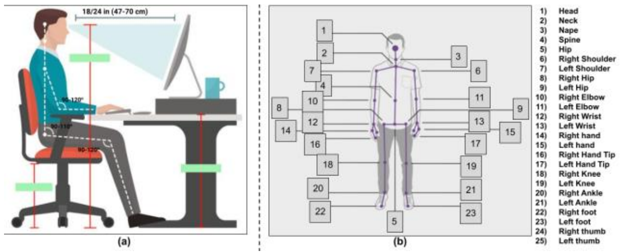

Figure 1. Standard sitting illustration (a), Kinect skeleton points (b)

In order to ensure that the sitting postures of the subjects are correctly changed during the experiment to apply the sitting positions specified in Table 1, a presentation containing the positions in Figure 4 was prepared. The subjects were asked to follow their sitting postures via this presentation throughout the experiment.

Experimental Setup and Software

Depth sensor-based data used for this study were collected with a Kinect camera. By using the depth camera, monitoring can be done without the user needing to install any equipment. An experimental setup was set up to create a depth sensor-based sitting posture database. In this setup, the subjects sit on a chair 1.5 meters from the Kinect device. They were requested to exhibit the postures defined in Table 1. Subjects waited for 30 seconds for each posture. The real-time data collection and recognition software (a) developed by Python, experimental setup (b), and presentation samples (c) are shown in Figure 2. The recognition software uses the TensorFlow machine learning library to create classification models.

Table 1. Definitions of sitting postures used in experiments

#	Name	Description	Ref.
1	Standard sitting	The hands were asked to sit on both armrests with the back fully leaned back and knees bent 90 degrees straight.	[11], [16], [17]
2	Leaning to the front side	They were asked to sit, so they bent forward as much as possible, avoiding contact with the back.	[11]–[14], [16]–[18]
3	Leaning to the left side	It was requested that the body be bent to the left by placing the right foot on the left foot and leaning the left arm on the armrest. The contact with the right sitting area was cut as much as possible.	[11]–[14], [16]–[18]
4	Leaning to the right side	The body was requested to be bent to the right by placing the left foot on the right foot and resting the right arm on the armrest. The contact with the left sitting area was cut as much as possible.	[11]–[14], [16]–[18]
5	Leaning to the backside	They were asked to sit and slide in the seat by creating a triangular gap in this area, in the form of cutting contact with the lower back and sitting back area.	[11]–[14], [16]–[18]

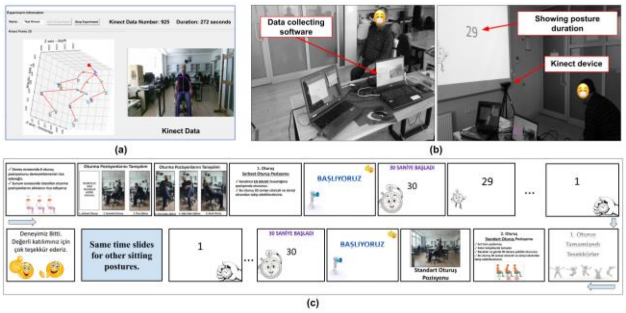

Figure 2. (a) Data collection software, (b) experimental setup, and (c) guide presentation

Labeling of Body Posture Data

Two approaches were used to label body posture. First, the traditional time-based approach was used. For this reason, the sitting posture signal of a subject was labeled by adding the start time of each subject to the duration of each sitting posture. Sample depth sensor signals of a subject are given in Figure 3. Dashed lines indicate signals of settling processes. When the time values are examined, it is seen that the subject does not take 30 seconds for each sitting position but more than 30 seconds for some postures. It was also observed in some other subjects.

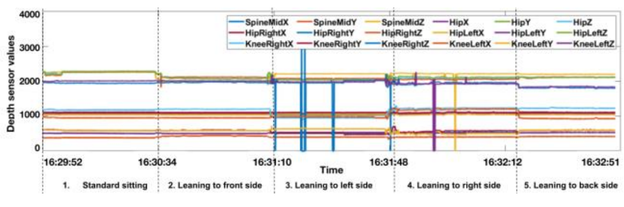

Figure 3. Example of a time-based depth sensor signal of sitting postures

The second approach is labeling sitting postures by using body limb angles in a fuzzy decision-making method while sitting. To apply the fuzzy-decision approach, the skeleton point positions were used to exclude body posture transition values from the data set and to label skeleton point data according to the definitions in Table 1.

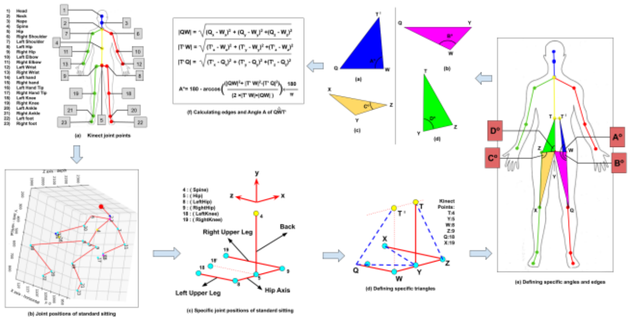

Figure 4. The skeleton points and the angles for standard posture

Each posture's specific angle values were selected to label using the skeleton points data. An example drawing and angle representation of skeleton point position data of standard sitting position is given in Figure 4. These angles have been defined respectively as the angle of the back with the left upper leg axis in the sitting position (A), the angle of the hip axis with the left upper leg (B), the angle of the hip axis with the right upper leg (C), and the left angle of the back with the hip axis (D). It was decided that these angles are the least number of angles that can represent incorrect sitting postures according to suggestions in [11], [15], [16]. Skeleton point location data is used as unit length, not actual length measures such as meters or inches. In order to calculate the angles A, B, C, and D, four triangles given in Figure 4 were formed, and the lengths of the sides forming these triangles were calculated. Since skeleton point coordinate information was obtained from the Kinect device in 3D space, the edge lengths of the triangles were calculated according to Equation 1 [19].

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2 + (z_2 - z_1)^2} \qquad (1)$$

For a triangle whose sides are A, B, and C, respectively, and each side has interior angles with the same name, angle A is calculated by Equation 2 [19]. According to the example triangle (a) given in Figure 4, whose side lengths were calculated with Equation 1, the value of angle A was calculated with Equation 2. Likewise, Equation 2 calculates the angles B, C, and D.

$$A° = 180 - arccos\left(\frac{|AB|^2 + |AC|^2 - |BC|^2}{2 \times |AC| \times |AB|}\right) \times \frac{180}{\pi} \quad (2)$$

During the experiment, raw data on the x (horizontal), y (vertical), and z (depth) axes of the 25 joint points of the subjects were obtained. The sample raw data of a subject and images of the skeletal pattern are presented in Figure 5.

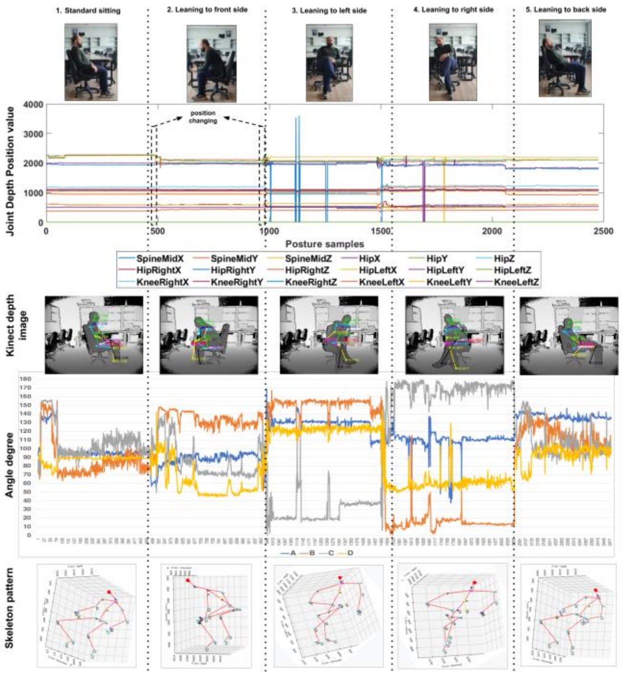

Figure 5. A subject's Kinect raw data as to sitting postures (between 1 and 2477 of supplementary data)

In Figure 5, the changes in the regions of the joint positions corresponding to the sitting positions for different axes values can be observed. The aim here is to determine the positions of the skeleton points of the subjects in the sitting position and to observe the proper sitting behavior with mathematical values instead of qualitative observation. The drawings were created as a result of axis rotation processes in order to make the skeleton point position drawings look more understandable in Figure 5. According to the angle range values determined by the recommendations in the literature in [11], [15], [16], the average angle values of the postures are given in Table 2; it is seen that angle values are suitable for the postures in Table 1.

Table 2. Angle values of sitting postures

Posture	1	2	3	4	5
Angle A	104.3	68.8	88.2	80.4	118.2
Angle A Range	95-105	65-90	85-90	85-90	110-120
Angle B	101.3	121.5	71.1	46.4	115.3
Angle B Range	95-105	110-125	65-80	40-60	110-125
Angle C	104.2	125.7	44.2	68.4	118.2
Angle C Range	95-105	110-125	40-60	65-80	110-125
Angle D	92.1	88.2	92.2	76.4	88.4
Angle D Range	95-105	85-100	85-100	70-80	80-90

Since the sides forming the B and C angles represent the upper legs mutually, these values should be close to each other. When the values are examined in Table 2, it is seen that this situation is achieved. At the same time, angle A is an angle that should decrease when leaning forward and increase when leaning back. Therefore, when the values are examined, they are calculated correctly, especially in the second and fifth sitting postures. It is also seen that the D angle values should not change much since there is not much bending to the right and left in the second and fifth sitting postures. For each pose recorded in the dataset, the angle values were calculated using the joint points in Figure 4.

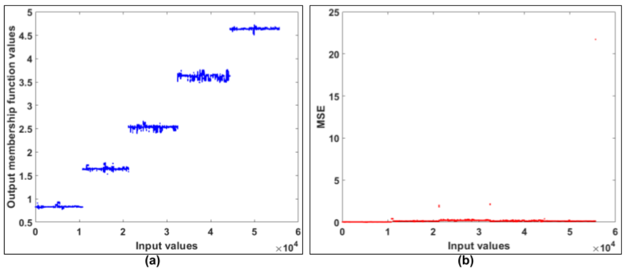

Figure 6. Fuzzy inference evaluation

Using SQL stored procedures, the sitting postures were labeled according to the angle ranges. Mamdani's fuzzy inference system is used in the fuzzy logic-based labeling approach. Four inputs are specified for each angle value. According to the angle ranges in Table 2, the Gaussian membership functions and the range of output variables for each class are defined as [0 5]. As the output variable membership function rules, range [0 1] for grade 1, range [1 2] for grade 2, range [2 3] for grade 3, range [3 4] for grade 4 and [4 5] range is determined for the 5th grade. The output results and MSE (Mean squared error) values after the designed fuzzy inference system's evaluation of the angle values are presented in Figure 6. When the charts are examined, it is seen that the classes are separated from each other due to the evaluation, and the MSE value is relatively low. Therefore, the fuzzy inference result labeled angle values clustered around their class as belonging to that class.

Selecting Features and Preparing the Dataset

After the fuzzy-rule-based labeling process, angular and geometric features from the upper body region were selected. This selection is because bottom body joint points like the hip can be unavailable due to office stuff like tables. Obtaining bottom body joint positions will be difficult when the study can be developed towards real-time application. Triangles were created using upper body joint points, and angle and distance attributes representing different seating positions were determined. The feature set is given in Figure 7.

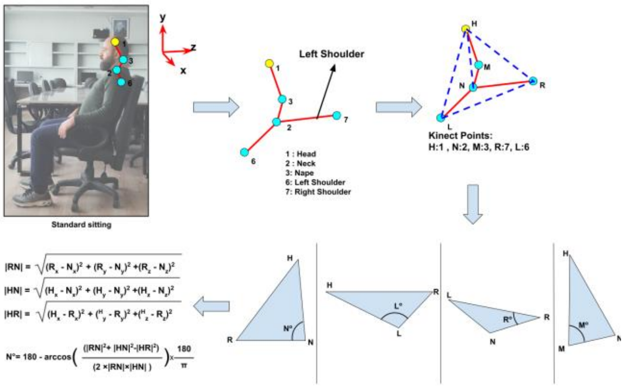

Figure 7. Calculation of angular and geometric features

The labeling and classification diagram is given in Figure 8. The depth sensor-based data of sitting body posture were obtained with an average 100 ms cycle (10 Hz). The field of view is 84.1 and 53.8 for horizontal and vertical, respectively. The depth distance is 3 meters.

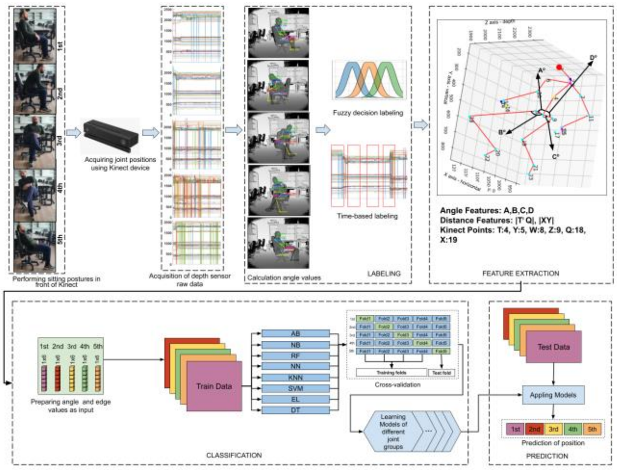

Figure 8. The general system diagram

It has been accepted that the lower body region meets the angle definitions made according to the standards and health recommendations in the literature given in Table 1. On the other hand, when the Kinect device is used in any office environment, access to the lower part of the body will inevitably be restricted due to office environment conditions. At the same time, it is clear that access to the upper part will be easier. For this reason, lower body angle values are used for labeling, while upper body angle features are used for feature extraction for classification. Since some subjects corrected their sitting positions during each sitting experiment, the angle values obtained from the skeleton point data were not at the desired values. Therefore, angle-based fuzzy decision labeling could not label these data for the determined sitting position. Different numbers of pose data were obtained for each class using time-based and fuzzy decision-based labeling. Time-based labeling is based on 30 seconds. Some subjects exhibited sitting behavior exceeding 30 seconds. Therefore, fuzzy decision-based tagging has more pose value than time-based tagging for each sitting class. 55649 and 33125 sitting body posture poses were obtained for 22 subjects in 5 classes by fuzzy decision labeling and time-based, respectively. The fuzzy decision labeling data set has 11130, 10115, 11220, 11957, and 11227 records for the first, second, third, fourth, and fifth postures, respectively. The data set of time-based labeling has 6748, 6167, 6703, 6727, and 6760 records for the first, second, third, fourth, and fifth postures, respectively. For all classifiers, 15% of the data was used as validation and test data. The training model has been tested with data not previously used in training. Therefore, test data is entirely different from training data. To recognize sitting body posture, shallow machine learning algorithms, the most widely used in the related literature, were used, and results were evaluated with performance indicators. Although deep learning methods gradually become overwhelming, shallow classifiers remain preferred because training time is shorter than deep learning methods [20]–[22].

Classification

In order to avoid depending on the solution of a single classifier in multi-class classification problems and to optimize the classification value, more than one classifier was used in this study. KNN, AdaBoost (AB), NN, Gradient Boosting (GB), DT, Quadratic Discriminant Analysis (QDA), NB, and Random Forest (RF) classifiers were designed and used to classify sitting postures. The classification models with different parameters were optimized and evaluated for best performance. For the KNN, model flexibility parameters such as the number of neighbors, distance metric, and distance weight have been chosen as 10, Euclidean, and SquaredInverse, respectively. The number of estimators and the learning rate are 50 and 1.5, respectively, for the AB model. The classification algorithms have been selected as SAMME.R. The regression loss function has been used as exponential. The NN model has 6 inputs, 100 hidden layers, and five output layers. Data division features random training function scaled conjugate gradient (SCG), Levenberg-Marquardt optimization method, and cross-entropy are used in the networks. The activation function is tan-sig, and the error goal has been limited to 0.001 [23], [24]. The weights and biases are initialized using the Nguyen-Widrow method. The number of trees is 200, and the learning rate is 0,02 for the GB model. The depth of individual trees is 5, and subsampling instances are 1. The maximum split parameter for the DT is 100. A minimum number of instances is 4 and 6 for leaves and internal nodes, respectively. The Maximum depth is 100, and the Gini Impurity Index has been used as the splitting criterion. The covariance structure is the complete option for Quadratic Discriminant Analysis. Kernel distribution has been utilized for the NB. The number of trees and the depth of individual trees are 50 and 10 for the RF model. All models were validated through a 5-fold cross-validation process. The cross-validation was performed without data sharing between training and validation data to avoid overtraining. In order to measure the performances of each model, a multi-class confusion matrix is defined in [25]. In order to measure the performances of each model, a multi-class confusion matrix, which is defined in [25] and the ROC curve, is created, and Accuracy (A), Recall (R), precision (P), F1-

score (F), AUC (Area Under Curve), and Specificity (S) indicators are calculated to evaluate performance [25].

Results and Discussion

For the classification of body postures, confusion matrices for the models are presented in Figure 9. Both training and testing processes were performed on the same computer. When the confusion matrices are examined, it is seen that the samples are mainly classified according to their classes.

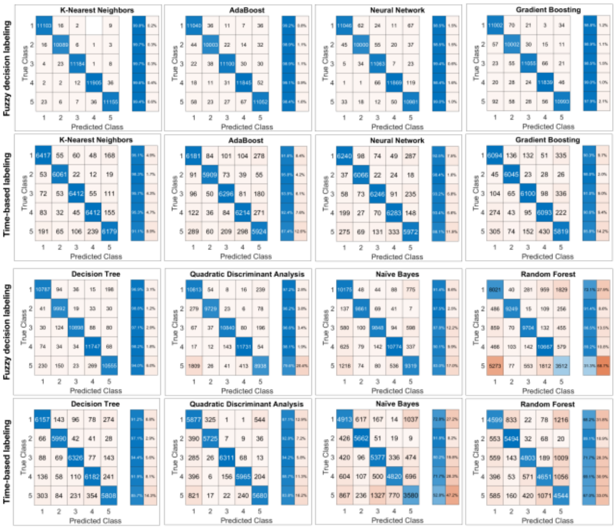

Figure 9. Confusion matrices of classifiers for datasets

It is seen that the first-class labeled samples are mainly classified as 5th class apart from their groups and vice versa for both datasets. Next, it is seen that the samples labeled as 3rd class are mainly classified as 2nd class and 5th for fuzzy decision labeling dataset, and 1st class and 5th for time-based labeling dataset, except for their groups.

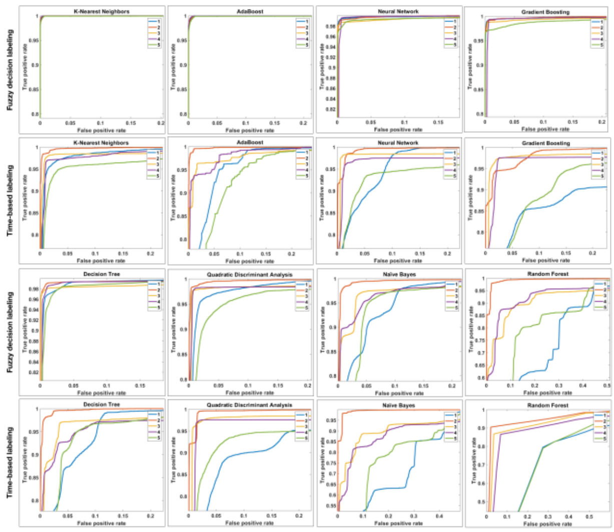

Figure 10. ROC curves of classifier

Except for their groups, the samples labeled as 4th class are mainly classified as 5th class for fuzzy decision and time-based labeling datasets. Finally, it is seen that the samples labeled as 5th class are mainly classified as 1st and 4th class, except for their groups. The ROC curves belonging to the models with the highest accuracy values for interpreting the accuracy values are presented in Figure 10. When the ROC curves are examined, it is seen that they confirm the confusion matrix values. For example, in confusion matrices (percentage section), the RF classifier has the worst values for both data sets' first and fifth classes. Likewise, when the ROC graph is examined, it can be understood that the first (blue) and fifth (green) classes have the worst learning success for the RF classifier since these graphs are far from the (0,1) point. When the ROC graphs are examined, it is seen that the KNN, NN, AdaBoost, and GB models are very close to the upper left corner point (0,1); therefore, the ability of these models to diagnose classes fits quite well. The classifier accuracy values are given in Figure 11. The other classifier performance metrics are given in Table 3.

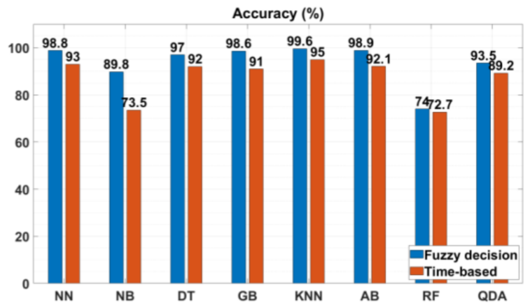

Figure 11. Classifier accuracies

When the performance of the classifiers is evaluated, if Figure 9, Figure 10, Figure 11, and Table 3 are examined, it is seen that the classification accuracy of the KNN classifier is higher than the other classifier for both two datasets. It is essential to visualize the decision-making rules of classifiers for multi-class classification problems in particular.

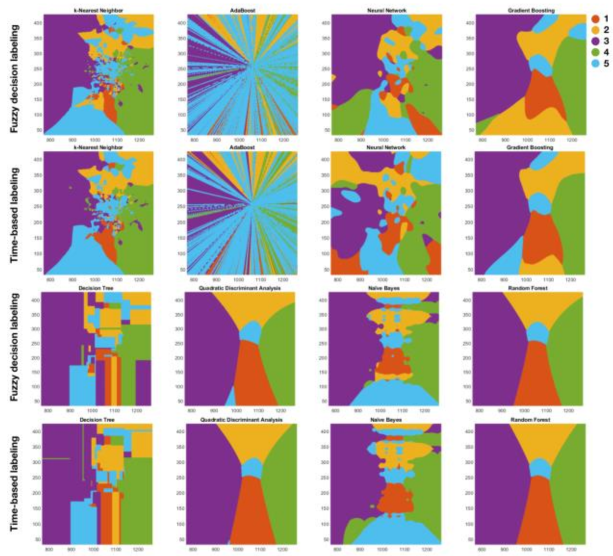

Figure 12. Classifier decision surfaces

Table 3. Classifier performance metrics

Dataset	Classifier	Accuracy	Precision	Recall	F-Score	Specificity	AUC	Train Time (seconds)	Test Time (seconds)
Fuzzy Decision	NN	98.760	0.98	0.98	0.99	0.99	0.98	446.94	0.235
	NB	89.808	0.89	0.89	0.97	0.93	0.89	0.452	0.078
	DT	96.999	0.97	0.97	0.97	0.99	0.98	2.014	0.009
	GB	98.638	0.98	0.98	0.98	0.99	0.99	416.44	0.6
	KNN	**99.617**	**0.99**	**0.99**	**0.99**	**0.99**	**0.99**	**1.484**	**4.23**
	AB	98.906	0.98	0.98	0.98	0.99	0.99	2.536	0.083
	RF	73.951	0.73	0.73	0.73	0.93	0.83	1.789	0.144
	QDA	93.534	0.93	0.93	0.93	0.98	0.95	2.41	0.034
Time-based	NN	93.002	0.93	0.93	0.93	0.98	0.95	56.809	0.077
	NB	73.515	0.73	0.73	0.73	0.93	0.83	0.1	0.011
	DT	91.964	0.91	0.91	0.91	0.97	0.94	1.633	0.004
	GB	91.022	0.91	0.91	0.91	0.97	0.94	109.656	0.237
	KNN	**95.037**	**0.95**	**0.95**	**0.95**	**0.98**	**0.96**	**0.234**	**0.993**
	AB	92.148	0.92	0.92	0.92	0.98	0.95	1.037	0.022
	RF	72.728	0.72	0.72	0.72	0.93	0.83	1.219	0.043
	QDA	89.232	0.89	0.89	0.89	0.97	0.93	1.35	0.014

*Green to red background: from the best to the worst

Therefore, to visualize the decision-making rules of the classifiers, artificial pose values were produced according to the minimum and maximum limits of the feature values of each class, and the models classified these. In this context, the classifiers with high classification accuracy values are expected to create more indented rule regions, and the lower ones will create less unindented rule regions. In this way, the decision surfaces presented in Figure 12 were created. When the rule areas given in Figure 12 are examined, it is seen that the most and least indented rule areas are formed by the KNN and RF classifiers for two datasets, respectively. In addition, the results of this study were compared with other studies in the literature and presented in Table 4. This study achieved a classification accuracy of over 99% and 95% by KNN for two datasets. In this context, classification accuracy values and other features obtained in studies in the relevant literature were compared with the results of this study and presented in Table 4. Dataset volume represents the total number of postures used as training and test data. The number of subjects indicates how many people were involved in experiments while the data set was created. The Joint Point is the skeleton point value used to create angular and geometric features to classify sitting positions. In Table 4, classification results and features using the datasets in this study are presented separately. When Table 4 is examined, it is seen that the highest accuracy value for the models used in both data sets was reached in this study. While there are studies in Paliyawan [6], Yao [8], and Li [9] with datasets more extensive than the dataset volume in this study, other studies used smaller-volume data. As a result, high accuracy values were obtained from studies in [6], Yao [8], and Li [9] with a larger volume than the dataset volume used. Although fewer joint points were used using the same labeling and classification method (KNN) than Bei's [10] study, higher performance was achieved. Better classification success was achieved using fewer subjects and fewer joint points than Li's [9] study. Compared to the other study in Paliyawan [6] using the NB method, the feature set with fewer joint points and a less voluminous data set was used, and a higher accuracy value was obtained. According to the sitting posture class type, this study has more class types than studies in Paliyawan [6], Pal [7], Li [9], and Ray [3]. Therefore, higher accuracy values were obtained compared to studies with the same or lesser class types.

Conclusions and Recommendations

Developing new, low-cost, accessible technologies is an essential step towards facilitating the assessment of sitting postures as office workers sit for extended periods. In this direction, standard sitting posture has been determined within the scope of relevant medical and health studies and standards to carry out the tests of the proposed system. Using the Kinect device, the depth sensor-based 98735 sittings pose data was obtained from 22 subjects for five different sitting positions, including the standard sitting posture. A fuzzy-logic labeling and traditional time-based method with depth-based angular features for labeling the sitting pose has been proposed. After labeling, angular and geometric features were obtained in the upper body region. In order to obtain the best classification accuracy, the sitting poses dataset with the minor joint points was classified using eight classification methods. A high classification accuracy value was obtained in most of the methods. In order to determine the relationship between emotional states and sitting postures, simultaneous data can be obtained by methods such as EEG [26], [27] and emotion detection-recognition, and their similarities can be investigated.

Table 4. Comparison of studies in the related literature

Study	Accuracy	Labeling Method	Feature Method	Classifier	Joint Point	Position Classes	Dataset Volume	Subjects
Yao [8]	86.6	AC	AF	Threshold	10	5	66330	10
Xia [5]	91.5	Histogram	LDA	HMM	20	5	6220	10
Pal [7]	94.3	AC	AF	CBD	16	2	5600	20
Ray [3]	94.8	AC	Grayscale image	LDA	12	4	22226	8
This Study	**95**	**Time-based**	**Angular - Geometric**	**KNN**	**5**	**5**	**33125**	**22**
Bei [10]	95.8	AC	Local contour -topological	KNN	6	9	16200	18
Paliyawan [6]	98.2	Automatic Time-based	Statistics	NB	10	2	397800	28
Li [9]	99.1	Geometric shape calculator	Body physical features	BP NN	8	2	55080	100
This Study	**99.6**	**Fuzzy Decision**	**Angular - Geometric**	**KNN**	**5**	**5**	**55649**	**22**
LDA: Linear discriminant analysis, HMM: Hidden Markov models, CNN: Convolution Neural Network, CBD: City-Block Distance, AF: Angular Feature, AC: Angular calculation								

The presentation of a depth sensor-based system prepares the infrastructure for a system that can be used in intelligent robot assistants, especially in robot vision. The system is thought to recognize sitting or other postures (bending, lifting, etc.) for those working in other fields. The proposed system is thought to be innovative and promising for detecting the sitting postures of office workers and presenting meaningful suggestions. The study proposes a new labeling process method to overcome the systems' shortcomings, which were proposed in previous studies involving joint points. The detailed results explain that this method is generalizable and can be used in joint point-based posture classification studies.

In terms of contributing to the literature, a comparison was made according to the features specified in Table 4, and it was revealed that this study is superior to other studies in the literature according to parameters such as accuracy, labeling method, feature method, classifier, joint point, position classes. Compared to the studies in the literature, it is thought that it contributes to the knowledge on the number of joint positions (provides low computational cost), the number of sitting postures class (proves the classification accuracy), and the labeling method (provides high accuracy). In addition, it is possible to mention some limitations of the system. Since the studies involving human subjects are limited to the number of volunteers participating in the experiments, it is planned to reach more people for data set expansion studies. In this direction, this study is considered a preliminary study. After the data set expansion studies, real-time potential use and performance tests in different environments will be performed, and the results will be discussed. In this way, it will be ensured that the system can be generalized in future studies, and its effectiveness in practice will be better evaluated. Limitations of the study include the ability to classify four incorrect sitting postures other than the standard posture. In addition, as another limitation of the study, according to the trained models, other incorrect postures that are different from the incorrect postures in the study can be classified according to these incorrect postures in real-time application. In this case, a measure such as a standard sitting score can be calculated by comparing the standard sitting posture classification rate with the rate of other postures in the real-time application. Obstacles may be encountered in the natural office environment (computer, panel, light, etc.) when obtaining the joint positions used as attribute values in creating the dataset. In addition, it may be difficult to obtain joint positions for rear-facing users. This may cause the classification model created with both the algorithm and the dataset to obtain incorrect results.

Ethics committee approval and conflict of interest statement

This work involved human subjects in its research. The ethics committee decision approved the methods and techniques used in this Uşak University Scientific Research and Publication Ethics Committee study dated 04.09.2020.

There is no conflict of interest with any person / institution in the article prepared.

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