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Balance Control Ability Evaluation and Center of Pressure Classification with Machine Learning Methods

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ABSTRACT: Athletes' balance control ability is essential in different sports. Effective analysis of athletes' balance control ability is an effective way for coaches and sports teams to identify subjects' skills. In the last few years, with the rapid growth of technology in sports, the necessity of using intelligent methods has increased. This study compares different artificial intelligence approaches to evaluate balance control ability by processing time-series data from the center of pressure. A recording pad collects center of pressure data from four types of subjects, ranging from professional skiers to non-athletes. Several experimental feature-extraction techniques were applied to the data, and the resulting features were used as input for artificial intelligence methods. This paper utilizes a multi-layer perceptron to classify subjects' skill levels. Compared with other methods, the multi-layer perceptron achieves more than 92% accuracy in classifying subjects' proficiency, yielding the best performance. Other methods, including k-nearest neighbors and support vector machines, achieved 72% and 69% accuracy, respectively. Analysis of center of pressure data can help identify promising individuals for real-world applications.

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1- Introduction

Balance control is an intricate process that is controlled by the interaction of various neurophysiological mechanisms [1]. These mechanisms adjust a special aspect of balance control, including "anticipatory postural adjustments" (APA), "reactive postural control" (RPC), "sensory orientation" (SO), and "dynamic gait" (DG), etcetera.

Standing posture is a complex system that concerns the maintenance of the relative positions of body segments. RPC indicates the capability to stay stable after the extrinsic factor. The use of numerous muscles and the integration of different sensorial inputs (visual, vestibular, proprioceptive) is a part of the complexity of this system [2]. In order to evaluate the subjects' performance, it would first require to be quantified. It is generally assumed that the body is relatively rigid and oscillates as a one-link inverted pendulum with the rotation axis at the ankle. In order to measure the balance ability, the center of pressure (COP) of the feet is widely used. The COP is analyzed using various statistical methods; the most common is calculating the speed of COP movement. The COP motions represent the net neuromuscular control or the subject's postural control. On the other hand, the next popular measurement is the area of the stabilogram (AOS) or confidence ellipse, which contains most of the COP data points. The AOS represents the subject's net performance: the smaller the surface, the better the performance [3].

Although several studies have examined the center of gravity (COG) or center of mass (COM) as complementary indicators of postural performance, evaluating these quantities often involves complex computations and estimation methods based on inverse dynamics or multi-link modeling. In contrast, COP-based analysis offers a more practical and widely accepted approach, especially in applied studies where ease of implementation and repeatability are crucial. For instance, Caron et al. demonstrated that although COM and COP exhibit distinct trajectory characteristics, COP remains a reliable proxy for neuromuscular control and is commonly used in standing posture assessments. Therefore, this study focuses exclusively on COP-based features, in line with its aim to explore accessible and interpretable classification models for balance evaluation 3].

Ren Et al. attempted to implement artificial intelligence to evaluate different types of balance control subsystems. First, the raw data were pre-processed to remove noise, and then 224 features were extracted. These features are divided into two groups: 1- Traditionally used features for the COP data (this part contains 124 features). 2- Features extracted from pixel-based COP displacement diagram (this part contains 100 features). Then, this feature set was applied to the regressors to map features to the evaluation scores provided by physical therapists [1].

In this study, Feature Extraction and Classification using artificial intelligence methods are the primary purposes. First,

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data collection and pre-processing are discussed; later, the feature extraction equations are applied to the raw data, and the feature set is prepared. Finally, three artificial intelligence methods were used to classify feature sets into four groups.

While previous studies have examined postural control across various conditions—such as visual deprivation, sensory manipulation, or equipment effects—many have primarily focused on comparisons between different sports or generalized balance assessments without directly addressing skill classification. In contrast, this study analyzes COP data collected from a mixed population including non-athletes, recreationally active individuals, semi-professional, and national-level skiers. This work uses three distinct machine learning models (MLP, SVM, and kNN) to classify athlete proficiency based on static postural data in both bipedal and unipedal positions. The proposed approach demonstrates how data-driven methods can be applied to differentiate performance levels in a way that may support training and monitoring strategies in applied sports settings.

2- Background and related works

Noe et al. examined the postural performance of two groups of male skiers at different expertise levels and measured the effects of postural control on the suppression of visuals. The subjects were seven national-level and seven regional-level skiers. They were asked to stand as still as possible on a force platform, with eyes open or closed, while wearing or not wearing their ski boots in 3 postures. One posture was the stable standing position, and two disturbance postures, generated via the seesaw device, induced instability in the Antero/posterior (AP) and Medio/lateral (ML) directions. The COP surface (90% confidence ellipse) and the COP velocity (sum of the cumulated COP displacement divided by test duration) were calculated [4].

Results of this study show that stability performance with ski boots is similar across postures for both groups, as indicated by no significant difference in COP surface. However, in the normal position (without boots), the COP surface was significantly greater for national-level skiers. Thus, regional skiers could be considered to have shown the best postural performance in these positions. The results obtained under normal conditions do not align with previous studies on expertise in sports and postural ability, as they show reduced postural performance as competition increases. This can be explained by the stiff alpine ski boots that competition skiers use, which act as external ankle support and mechanically restrict ankle joint motion. Moreover, this study's results revealed no interaction between the expertise level and visual condition factors [4].

On the other hand, Asseman et al. examined fifteen gymnasts in three postures: bipedal, unipedal, and handstand with open eyes to determine the correlation between the level of athletes and COP surface and mean COP velocity. This research was derived from the fact that postural performance and control are not related to the expertise level of athletes [2].

Andreeva et al. investigated the postural stability of 963 athletes (aged 6-47 years) in fourteen different sports fields [5]. The test was performed with eyes open and closed, in a bipedal posture. Based on the velocity of COP with open eyes (VCOP-EO), the result indicates the postural stability of athletes as below:

Shooting < football < boxing < Cross-Country Skiing < gymnastics < running < Team Games Played with Hands < wrestling < tennis < alpine skiing < rowing < speed skating < figure skating.

Caron et al. examined seven healthy male subjects (non-athletes) to understand the relationship between the center of pressure and the center of gravity (COG). They investigated the trajectory path of COP and COG in the frequency and time domains. Besides, their experiments examined whether the COP variable was sufficient for analyzing the balance control. Caron et al. showed that there is no linear relationship between COP and COG, but the COG is related to the frequency and amplitude of the COP motion. Also, the COP is an insufficient variable to analyze sensory performance and balance control thus, simultaneous analysis of the COP surface and COP motion velocity is necessary [3].

Agostini et al. investigated 46 volleyball players and 42 non-athlete subjects with different visual and posture conditions. This research defines multiple parameters based on COP: mean velocity, sway area, root-mean-square values for the two axes, minor and major, and the eccentricity of the smallest ellipse 6].

Paillard et al. analyzed eight high-level professional soccer players and nine regional soccer players in reference conditions and in manipulated sensorial conditions with eyes open or closed. To manipulate the normal condition, each subject put his feet in a bucket of ice and water (5 degrees Celsius), stayed on a force plate, and measured the surface and velocity of COP motion. Results show that high-level soccer players have better postural control in both conditions [7].

On the other hand, Davlin performs a test on 57 gymnasts, 58 soccer players, 70 swimmers, and 61 non-athletes. Subjects' characteristics included height, weight, shoulder width, age, and training time, and the non-athlete group served as the control group. Dynamic balance was assessed on a stabilometer for 30 seconds per subject, and the test was repeated 7 times. The stabilometer recorded the time the participant held the platform within 5° of horizontal on either side. They considered sex as not related to balance control. Also, the result shows that gymnasts have better stability than soccer players and swimmers, respectively [8].

There is another application of COP pressure sensing: Qian et al. designed an approach for people recognition based on gait and 3D COP. 3D COP contains the pressure profile and location of the pressure point for each foot. They collected ten subjects, extracted five key points, and defined four feature sets to train the proposed classifier method. The proposed method is the binary version of linear discriminant analysis, called Fisher Linear Discriminant (FLD), and the best accuracy reported is 94.2 percent 9].

Table 1. Information for the subject dataset used in this paper.

Subject level	Number of subjects	Age	Class Code	Sampling frequency
National team member	4	19.45±5.0	A	100 Hz
Semi-professional	16	21.43±3.98	B	100 Hz
Normally trained	6	20.04±4.6	C	100 Hz
Common person	8	21.81±3.8	D	100 Hz

Human motion analysis can also be used in robotics. Ferreira et al. acquired images of a walking person fitted with a set of white light-emitting diodes (LEDs). The acquired trajectories of the light points were then used to specify joint trajectories in a bipedal robot. Ferreira et al. also developed a system to acquire the center of pressure. This system uses eight force sensors, four under each foot. The influence of the human torso angle on the COP position during walking was confirmed. Data was used in a support vector regression (SVR) method for biped robot sagittal balance control [10], [11].

Zhang et al.'s research criticized the use of raw COP data and presented an implementation of the Poincaré plot for measuring COP trajectories, and validated its effectiveness through tests. The validation was conducted on 136 healthy adults, and the data were categorized based on age and open or closed eyes. The results suggested that the Poincaré analysis of posturography (the trajectory of the COP plot and its confidence ellipse) provided in-depth information on posture control using nonlinear indic [12].

Besides eye and physical distortions, other disturbances can affect the balance of even elite athletes. In Viseux et al.'s research, a novel disturbance was considered. The effects of a small additional thickness placed under the great toes were evaluated on the COP and balance parameters in 14 elite women's handball players. Features that are extracted from COP were (i) the surface of COP excursions, (ii) the frontal (X) mean position of the COP, (iii) the sagittal (Y) mean position of the COP, and (iv) the mean speed of the COP. Results show that adding 0.8 mm under both toes significantly decreases COP surface and mean velocity, but there is no difference in COP X and Y positions [13].

In summary, previous studies have primarily investigated postural stability across various sports or conditions such as footwear, visual occlusion, or sensory manipulation, often using COP features to describe general balance performance. While some employed basic statistical analysis, few applied machine learning techniques, and even fewer conducted classification tasks. Moreover, many studies focused on elite athletes or specific groups, without considering a mixed population across skill levels. However, this research analyzes COP data collected from a diverse group, including non-athletes, semi-professionals, and national-level skiers, and applies multiple machine learning classifiers to evaluate proficiency based on static postural tasks. This structured approach enables a more comprehensive and practical assessment of balance control in athletic screening and training contexts.

3- Method and data

This paper aims to classify the COP of subjects into four groups using intelligent classification methods. First, data collection and experimental tests are discussed. After that, the raw data is pre-processed in MATLAB and windowed using two different time steps. Then, the feature extraction operation is applied to the data to find individual characteristics of the subject's COP pattern during each window. During the feature extraction step, 28 features are extracted to train the proposed methods. Finally, the result of each classifier is reported and compared.

3- 1- Data Acquisition

This paper uses a dataset collected from 34 real freestyle skiers from China's national team and three other groups to validate and compare the proposed method with other subjects' balance control ability. The dataset contains four different groups of subjects, and each group has a different number of members. The details of the dataset are shown in Table 1. Also, the participants had an average height of 169.1 ± 10.0 cm and an average weight of 64.8 ± 11.1 kg (n=34).

In the experimental study, subjects were asked to stand on a balance meter for 30 or 45 seconds, with two feet at the first trial and one foot (left foot) at the second trial, and to try to maintain their best balance. The area of the balance meter is 65 cm × 40 cm and can record data in anteroposterior and mediolateral directions, named x and y in this paper, respectively. The dataset is divided into four different levels of athletes. The subjects were from various groups, including high-level skiers from China's national team, semi-professional skiers, normally trained athletes, and common people.

These four groups are mentioned as A, B, C, and D, respectively. Clearly, the balance control ability increases from D to A. For example, group A has the best balance control ability. Fig. 1 shows one subject standing on his left foot while measuring COP on a record pad. Each athlete stands in two conditions, standing upside down and straight on two feet. This test condition is named 'both' in this paper.

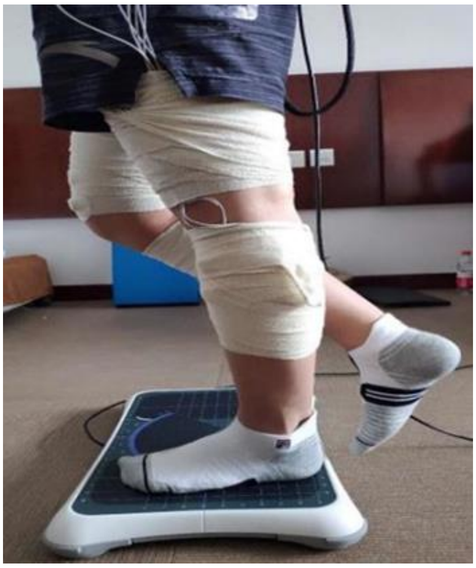

Fig. 1. Test procedure for standing on the left foot.

Next, the same individual is standing on his/her left foot, as shown in Fig. 1. This posture is named ‘left’ through the context. The standing pad records the center of pressure of subjects over time. Fig. 2 is the schematic of the COP of one subject from each class. As shown, the athlete with a higher professional level had much less displacement in each axis. After data collection, feature extraction operations are applied to raw data, and the statistical features are extracted.

3- 2- Pre-processing

The raw data did not require any additional filtering, normalization, or outlier removal, as it was recorded under controlled experimental conditions and was sufficiently clean for analysis. In order to increase data samples, the windowing method was applied to each individual subject. For f1-f9 features, a window length was selected as two seconds and three seconds was selected for features that are calculated by the difference of displacements (f10–f27). The reason for choosing two different time intervals for windowing is that, when calculating the f10–f27 features, if the window length is too short, the feature values decrease significantly. Besides min, max, and mean in AP/ML directions, there is the distance that is defined as Eq. 1:

$$mag = \sqrt{(x^2 + y^2)} \tag{1}$$

Where x and y pair could be displacements, velocity, or acceleration in AP and ML direction, respectively. In order to calculate velocity (acceleration) in each direction, the related sequential displacements (velocities) were subtracted. Since the time step during the data acquisition was fixed, dividing all values by the time step does not affect classification results. Because the velocity and acceleration data were not divided by the time step, they were represented by Δ and Δ^2, respectively.

The confidence ellipse was calculated using all data for each window and in both AP/ML directions. The confidence interval for one direction was defined as Eq. 2:

$$CI_x = \bar{x} \pm z s_e \tag{2}$$

Where CI_x is the confidence interval of the x data and $\bar{x}$ is the average value of x (displacement in the AP/ML direction). z coefficient shows the confidence levels (for instance, it is 1.28 for an 80% confidence interval). S_e is the standard deviation of the dataset and is calculated independently.

In Fig. 3 and Fig. 4, the mean of the confidence ellipse areas is illustrated based on the level of skiers and the foot that was tested, respectively.

3- 3- Feature Extraction

In order to classify the COP of subjects, 28 features were extracted from the collected COP data, which are illustrated in Table 2. To evaluate the individual contribution of each extracted feature to model performance, a leave-one-feature-out (LOFO) sensitivity analysis was performed. For each feature i, the classifier was retrained after omitting only that feature; the resulting loss was compared with the baseline loss obtained with the full feature set. Results are based on single LOFO retraining runs per feature; therefore, they are presented as sensitivity indicators rather than formal statistical estimates.

Four groups of datasets are defined in this study: displacement, velocity, acceleration, and confidence ellipse. The first three dataset groups have been extracted through x (AP) and y (ML) directions with the Euclidean distance. For each direction /distance, the minimum, maximum, and mean of the window array were calculated as a feature. Therefore, each dataset has nine values. Ren et al. used a range of AP/ML directions as features for their study [1], but in this paper, due to the increasing features, minimum and maximum values were selected instead of the range of motion.

3- 4- Pattern Classifiers

This section briefly explains the pattern classifiers proposed in this paper, then describes the architecture and parameters of each classifier. Pattern classification tasks are divided into generative and discriminative categories. Generative models are among the most important domains in machine learning and computer vision, and they are highly informative. In complex problems where the input vector has a wide range, it is difficult to assign a label to all data. Thus, we can use a generative model that produces a joint distribution over the input data and the class label.

Discriminative models are generally used for classification tasks, not for synthesizing samples of interest. These models have good classification or discrimination task performance, but their modeling capability is limited because they focus on decision boundaries. This paper uses two discriminative models (kNN and SVM) and one generative model (MLP)

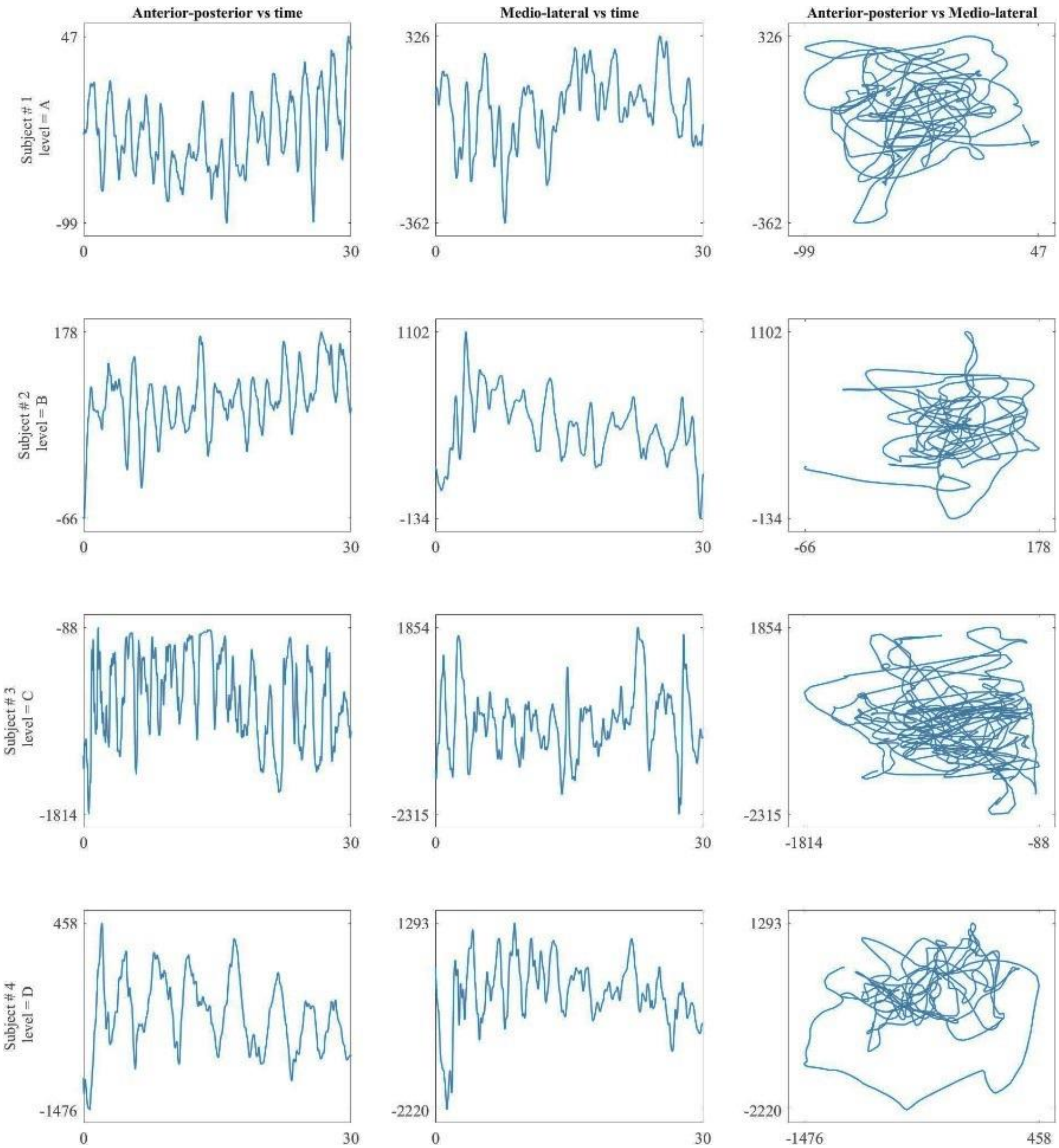

Fig. 1. Position of COP in AP/ML directions (time unit = sec, displacement unit = mm)..

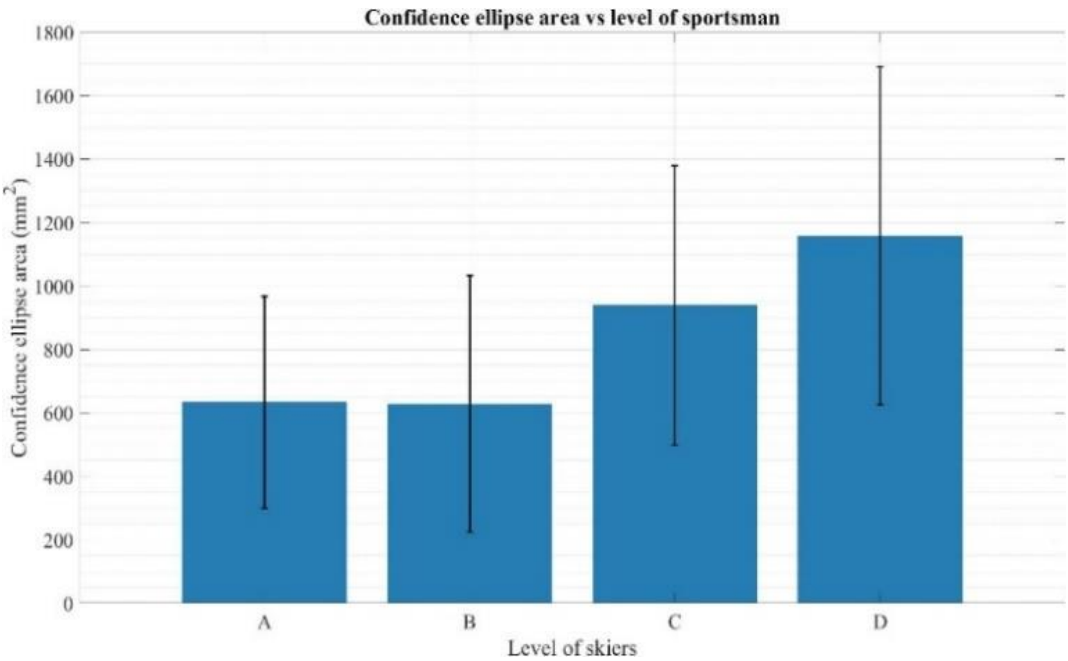

Fig. 3. Average confidence ellipse area based on the level of the sportsman.

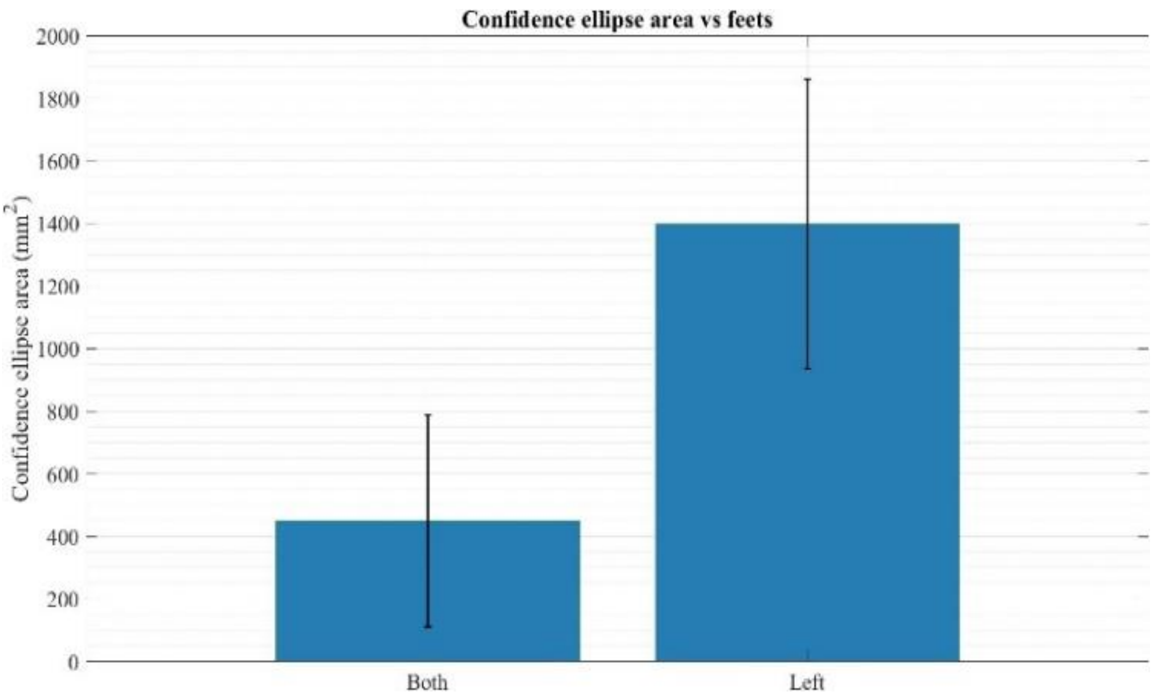

Fig. 4. Average confidence ellipse area based on the foot standing on it during the test.

Table 2. Features and description.

Feature	Description	Variable name	Variable sensitivity analysis (normalized)
F1	The minimum of the COP displacements in the AP direction	x_{min}	27.59
F2	The maximum of the COP displacements in the AP direction	x_{max}	62.06
F3	The mean of the COP displacements in the AP direction	x_{mean}	15.21
F4	The minimum of the COP displacements in the ML direction	y_{min}	29.22
F5	The maximum of the COP displacements in the ML direction	y_{max}	31.42
F6	The mean of the COP displacements in the ML direction	y_{mean}	22.44
F7	The minimum distance of the COP displacements in the AP-ML direction	mag_{min}	70.32
F8	The maximum distance of the COP displacements in the AP-ML direction	mag_{max}	32.02
F9	The mean distance of the COP displacements in the AP-ML direction	mag_{mean}	59.46
F10	The minimum COP velocity in the AP direction	Δx_{min}	5.52
F11	The maximum COP velocity in the AP direction	Δx_{max}	82.59
F12	The mean of the COP velocity in the AP direction	Δx_{mean}	53.02
F13	The minimum COP velocity in the ML direction	Δy_{min}	19.90
F14	The maximum COP velocity in the ML direction	Δy_{max}	0.38
F15	The mean of the COP velocity in the ML direction	Δy_{mean}	40.28
F16	The minimum distance of the COP velocity in the AP-ML direction	Δmag_{min}	23.59
F17	The maximum distance of the COP velocity in the AP-ML direction	Δmag_{max}	22.24
F18	The mean distance of the COP velocity in the AP-ML direction	Δmag_{mean}	100.00
F19	The minimum COP acceleration in the AP direction	$\Delta^2 x_{min}$	48.95
F20	The maximum COP acceleration in the AP direction	$\Delta^2 x_{max}$	44.31
F21	The mean of COP acceleration in the AP direction	$\Delta^2 x_{mean}$	13.37
F22	The minimum of COP acceleration in the ML direction	$\Delta^2 y_{min}$	78.51
F23	The maximum COP acceleration in the ML direction	$\Delta^2 y_{max}$	16.31
F24	The mean of the COP acceleration in the ML direction	$\Delta^2 y_{mean}$	7.00
F25	The minimum distance of the COP acceleration in the AP-ML direction	$\Delta^2 mag_{min}$	42.63
F26	The maximum distance of the COP acceleration in the AP-ML direction	$\Delta^2 mag_{max}$	19.88
F27	The mean distance of COP acceleration in the AP-ML direction	$\Delta^2 mag_{mean}$	29.62
F28	85% confidence ellipse area (mm^2)	CE	21.11

[14], [15], [16].

k-Nearest Neighbor (kNN): One of the simplest and easiest-to-implement methods for classification is the k-nearest neighbor, also known as lazy learners. kNN does not need a training step and classifies by making a decision. The classification operation is by finding a group of k objects in the training data that have the most similarity to the test data, and assigning the label of the training data to the test object. Finding the best number for k is a challenge because small k can be sensitive to noise, and large k may include more classes. Another challenge for this method is to assign the right label to an object. As mentioned above, k is a group of classes that, based on the selected criteria, are closest to the test objects. For assigning a label to test objects, the number of classes that exist in k should be counted, and the most frequent class that is counted in k should be selected as a label of the object. The simplest way is to count each class in k and choose the most voted class[15], [17].

Multi-layer perceptron (MLP): In recent years, artificial neural networks (ANNs) have been used for regression, prediction, and classification tasks. These methods are generally based on biological systems and research on how the human brain works. ANNs are very reliable methods for learning from imperfect or incomplete data and have shown good results; therefore, they are useful for investigating data from the real world, including natural noise [18]. A multi-layer perceptron (MLP) is an ANN used in this paper. MLP is a feed-forward neural network that includes an input layer, and the number of neurons in this layer is calculated based on the data size. Then, hidden layers are employed to process data (one or multiple layers), and the last layer is utilized to map processed data to the correct class. In the training step, the data is fed to the input layer, which sends the resulting information to hidden layers, and at the end, the processed data is sent to the output layer to characterize the class of data. For more details, see [19].

Support Vector Machine (SVM): As mentioned, discriminative classifiers have superiority in the classification task. SVM is one of the feed-forward and supervised classifiers that is used in many classification problems. The linear support vector machine tries to find the best hyperplane to separate data and assign +1 or -1 to each class $\{x_i, y_i\}, i = 1,2,...,l, y_i \in \{-1,+1\}, x_i \in \mathbb{R}^d$. This method calls one-against-rest and is used for data that is linearly separable. The separating hyperplane Eq. 3 has two parallel lines with a margin size of d called positive Eq. 4 and negative Eq. 5 support vectors [20], [21].

$$w.x + b = 0 \tag{3}$$

$$x_i.w + b \geq 1 \text{ for } y_i = +1 \tag{4}$$

$$x_i.w + b \leq 1 \text{ for } y_i = -1 \tag{5}$$

Where w is normal to the hyperplane and $|b|/\|w\|$ is the perpendicular distance from the hyperplane to the origin. Fig. 5 shows the separator line and support vectors.

While a variety of other approaches, such as ensemble methods, are also commonly applied in classification tasks, they were not considered in this study due to the relatively small dataset size, which could increase the risk of over fitting in such models. The selected classifiers represent three well-established and complementary paradigms in machine learning: a distance-based method (kNN), a margin-based classifier (SVM), and a neural network capable of modeling nonlinear relationships (MLP). This combination provides both simplicity and robustness, making it suitable for evaluating balance control with limited data samples.

3- 5- Pattern Classifier Implementation

This paper utilized MLP, kNN, and SVM as pattern classifiers to classify the dataset. These pattern classifiers are implemented in the Python programming environment (V 3.10). kNN and SMV use the SKlearn Python library,

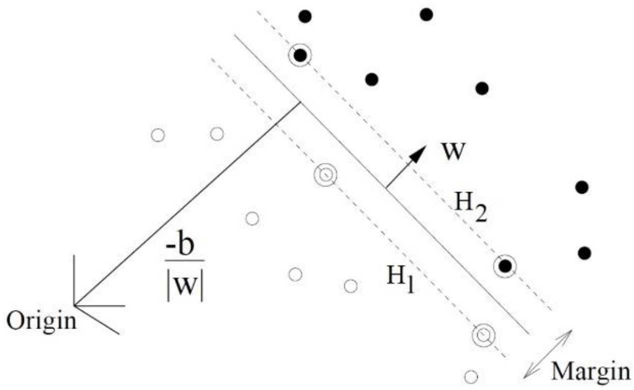

Fig. 5. Linear separating hyper planes for the separable case. The support vectors are circled [20]

and MLP is implemented in the Tensor Flow framework and Keras library. Parameters and the structure of pattern classifiers are determined by trial and error. A summary of pattern classifier parameters and structure is shown in Table 3. The goal of the classifiers is to determine the level and foot that are used during the test. In fact, there are eight foot-level clusters, two for foot (left and both foots) and four clusters for levels (A, B, C, and D).

In this paper, kNN is set for five nearest neighbors, and SVM uses the Radial Basis Function (RBF) as the kernel. The structure of MLP is more complicated. This classifier has a hidden layer with a seven-neuron output layer that contains two neurons. The role of the last layer of this model is to decide which label should be assigned to the input data. The role of the last layer of this model is to determine which label should be assigned to the input data. The output of the MLP classifier is a vector with two values that show the proficiency level of the subjects and their standing posture.

All classifier parameters were determined empirically through repeated experiments and validation on the dataset. The reported values represent the settings that consistently provided stable training and reliable classification performance. This approach follows common practice in machine learning when the dataset size does not allow for extensive grid search [22].

4- Results

In Table 4, the results for each of the classifiers are illustrated. Despite the fact that the MLP classifies standing posture and skier level together, it performs better than SVM and kNN. SVM and kNN achieve higher accuracy in posture classification than in level classification. The macro-average of precision, recall, and F1-score is also reported in this table because MLP produces a two-dimensional output; calculating those parameters is not possible.

Fig. 6 and Fig. 7 represented the confusion matrix for SVM and kNN classifiers, respectively. In these confusion

Table 3. Methods and structures.

Method	Parameters and structure
MLP	- Sequence of layers and number of neurons = {14, 7, 2} - Learning rate = 0.1 - Loss function = Binary Cross Entropy - Arrange of activation functions = {relu, relu, sigmoid} - Batch size = 16 - Epochs = 15 - Validation size = 0.2 of all with shuffle
kNN	- Nearest neighbor value k = 5 - Metrics = Minkowski - Power = 2 /Euclidean distance
SVM	- Gaussian RBF kernel - $\gamma = {}^{1}\!/_{n_{feature}}(28).\text{variance}$

Table 4. Results for the classification of each method.

Method	Class	Accuracy (%)	MSE	Precision	Recall	F1-score
MLP	Level & foot	92.15	0.97	-	-	-
kNN	Level	72.67	0.61	0.70	0.71	0.70
	Foot	93.60	0.25	0.94	0.93	0.93
SVM	Level	69.76	1.38	0.78	0.59	0.61
	Foot	90.98	0.28	0.92	0.90	0.90

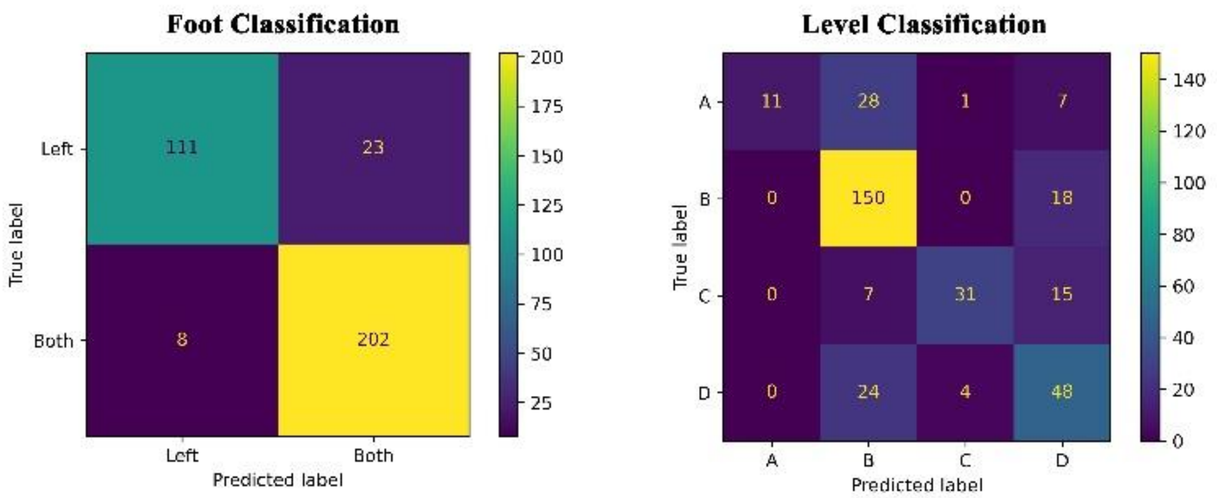

Fig. 6. SVM confusion matrix.

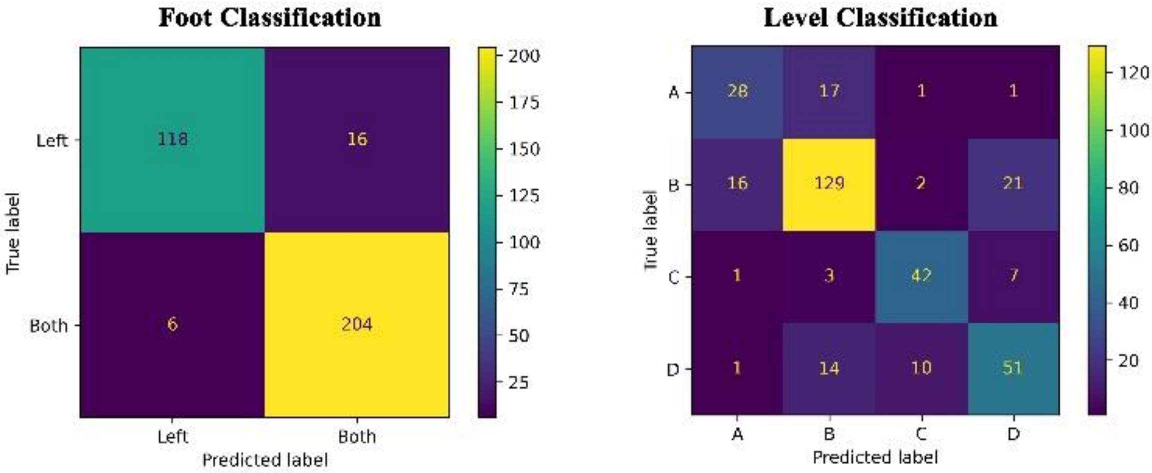

Fig. 7. kNN confusion matrix.

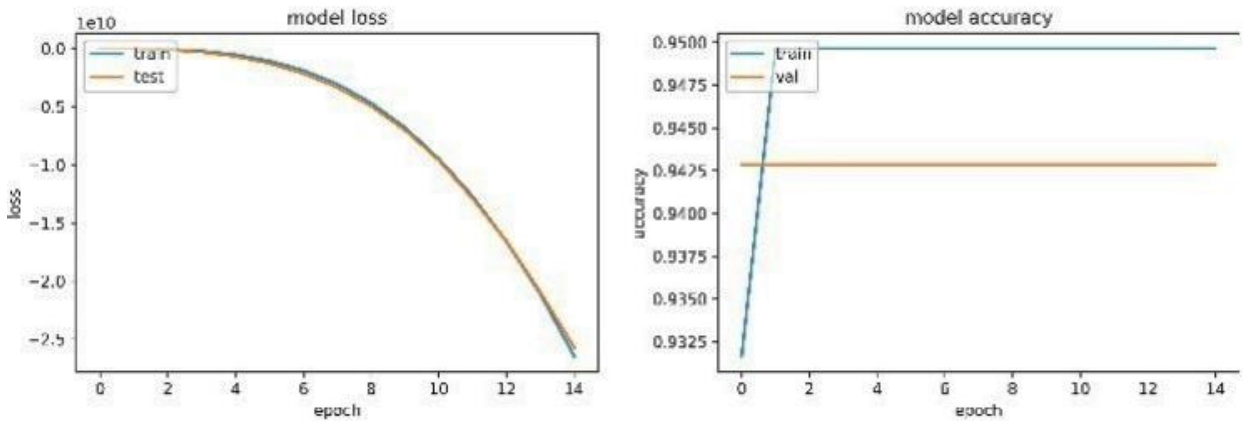

Fig. 8. Provides MLP loss and accuracy according to epochs.

matrices, as illustrated, if skiers are more experienced, classification is much easier for the algorithms. However, the MLP's confusion matrix is three-dimensional, so it cannot be illustrated here.

To examine the robustness of the reported accuracies, an additional validation was performed by adding controlled variance to the original dataset (σ = 0.15, μ = 0, Domain proportional = 1/20). When models were re-evaluated on this perturbed dataset, the MLP classifier maintained an accuracy of 82.15%. This result indicates that the performance advantage of MLP is not solely dependent on the specific characteristics of the training data, but remains stable under data variability.

An analysis of the misclassifications reveals that errors were most frequent in the classification of athlete proficiency levels, particularly between adjacent groups such as semi-professional and normally trained skiers. This suggests that COP patterns in these categories share overlapping characteristics, which may limit the separability of features. In contrast, national-level athletes were classified with higher reliability, suggesting more distinct balance-control signatures. Posture classification showed fewer errors across all methods, reflecting the clearer differences between single-leg and double-leg stances. These findings highlight that future improvements could focus on refining feature extraction to capture subtle differences between similar proficiency levels, or on employing advanced model architectures designed to enhance class separability.

When comparing these results with prior research, some notable similarities and differences emerge. Earlier studies often examined postural control under sensory manipulations, such as vision removal or unstable platforms [2], [4], while the present work focused specifically on distinguishing athlete proficiency levels from COP signals. Ren et al. [1] applied artificial intelligence to COP data with a larger set of extracted features, but their aim was to map performance scores from therapists rather than to classify expertise levels directly. In contrast, the present study shows that a reduced feature set combined with machine learning classifiers can still achieve strong accuracy, particularly with MLP. Although MLPs are well-established in general machine learning applications, their use in the context of balance control assessment provides new insights: the ability to simultaneously classify both the posture condition and the proficiency level. This distinguishes the approach from previous work that relied on single-dimensional analyses or traditional statistical features. Furthermore, while Caron et al. [3] suggested that COP alone may be insufficient to capture balance control, our results demonstrate that COP-based features remain informative for distinguishing between groups of athletes, especially at higher proficiency levels. Together, these comparisons suggest that the proposed approach complements existing findings and contributes a novel perspective to athlete evaluation.

5- Conclusion

This study applied three different classifiers to 34 skiers' COP data to examine the sportsmen's proficiency level. The classification was based on a feature set containing 28 features proposed in Section 3.3. Raw data was collected with a 100Hz frequency on a record pad in 30 or 45 seconds. In order to increase the number of data samples, the windowing method was applied to each subject, as explained in section 3.2.

Second, in this paper, three pattern classifiers were applied to the dataset. Multi-layer perceptron (MLP), support vector machine (SVM), and K-nearest neighbor (kNN) were suggested for the classification task.

SVM was trained to classify the foot and level of athletes separately, although kNN tries to assign the right foot or level label to subjects apart. On the other hand, because MLPs are capable of classifying complex data, they were trained to simultaneously recognize level-foot labels. As expected, artificial neural networks performed better in this classification. Average foot-level accuracy was 92.15%, 82.13%, and 80.37% for MLP, kNN, and SVM, respectively.

The most important application for our study is to define each subject's proficiency before entering this field of sport. Although there is a possibility for people to be selected for the sports field in which they are more likely to succeed. On the other hand, with these algorithms, the athlete with the greater likelihood of success in competitions can be selected. These methods can be used to train an athlete and their assistant. When an athlete is injured, the analyzed COP data can help coaches and assistants determine whether the athlete has fully recovered.

It should be noted that the real-world deployment of COP-based classification systems may face challenges related to sensor accuracy, environmental conditions, and inter-individual variability. Laboratory-grade force plates can reduce noise and enhance precision, but field applications may introduce additional uncertainties. Addressing these factors will be essential for translating the present findings into reliable, practical tools. Future studies could extend this work by incorporating additional physiological measurements alongside COP data or by applying deep learning approaches to capture complex patterns in balance control better.

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