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RESEARCH ARTICLE

Exploring Achilles Tendon Vibration Data Classification for Balance Training: A Wavelet-Based Machine Learning Approach

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ABSTRACT Balance training is widely used to improve stability, and Achilles tendon vibration is an effective method. However, evaluation of training progress often relies on Center of Pressure (COP) analysis, which can be challenging for non-experts. To provide an objective and automated assessment, this study explores machine learning techniques. Achilles tendon vibration was applied during standing, and COP data were collected under various conditions, including eyes open/closed and cognitive/non-cognitive tasks. To more accurately assess the training effects, this study applied machine learning techniques that combine wavelet decomposition for feature extraction. Three genetic algorithm-based machine learning models (GA-SVM, GA-LGBM, and GA-LR) were constructed for feature selection and classification. The results showed that all three models achieved classification accuracies above 80% in identifying Achilles tendon vibration and non-vibration data, with SVM achieving the highest accuracy of 89.59%. Among the selected features, entropy category features played a crucial role, and entropy values were higher under Achilles tendon vibration conditions than under non-vibration conditions. This study confirms the feasibility of applying machine learning to Achilles tendon vibration rehabilitation training in the future, and the identified key features also provide a theoretical basis for the analysis of Achilles tendon vibration data. These findings provide valuable insights for further optimization of balance rehabilitation training programs.

INDEX TERMS Balance, Achilles tendon vibration training, machine-learning, genetic algorithm, feature selection, wavelet discrete decomposition.

I. INTRODUCTION

Maintaining balance while standing is a complex and critical aspect of human motor control [1]. The ability to maintain postural stability is essential for daily activities and coordinated movements. Impaired balance increases the risk of falls [2], which not only result in physical injury, but also cause fear of falling. Fear of falling can lead to decreased confidence, activity avoidance, and social isolation, which can exacerbate mental health problems such as anxiety

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and depression [3]. To improve balance and reduce the risks associated with balance disorders, balance training has become a widely used approach [4], [5].

Achilles tendon vibration training as a form of balance training has been shown to improve neuromuscular coordination, modulate neurotransmitter release, and promote neuroplasticity, making it a promising approach for improving balance control [6], [7]. During training, the measurement of center of pressure (COP) related metrics is a common evaluation method [8], [9], [10]. COP represents the center of pressure on the body, and analysis of its variations provides insight into an individual's balance status while standing. However, for the general population, understanding the meaningful interpretation of these complex data metrics can be challenging. As a result, effective balance training typically requires the guidance of physical therapists (PTs). However, when individuals engage in home-based balance training, PTs often provide exercise plans and individuals must perform self-assessments to determine their progress. Due to the lack of feedback from PTs, self-assessments may be inaccurate, leading to slow training progress and compromising the overall effectiveness of the program [11], [12].

In order to provide a more comprehensive, objective, and automated approach to training evaluation, some researchers have recently applied machine learning (ML) techniques to the analysis of balance data. Peng Ren et al. attempted to evaluate balance control subsystems (BCS) using artificial intelligence and demonstrated its potential applications in clinical settings by analyzing center of pressure data [13]. Tian Bao et al. manipulated visual, foot, and support surface conditions, recorded balance data using inertial measurement units (IMUs), and achieved classification of balanced and unbalanced states [12]. However, targeted analysis of Achilles tendon vibration data during the standing balance task using machine learning techniques has not been investigated.

Machine learning uses large amounts of training data to learn patterns and features within the data, enabling the construction of models that can automatically recognize and classify data [14]. Classification model performance metrics, such as accuracy, reflect the differences or separability of the data. Higher accuracy indicates greater dissimilarity between different classes of data, allowing the model to effectively classify them. Given the individual differences in response to Achilles tendon vibration training, the differences between non-vibration and vibration data may vary between individuals, resulting in different classification results [15]. To achieve better training results, it is necessary to adjust vibration frequency, intensity, or other training parameters based on individual differences. In addition, flexible adaptation of training parameters during different stages of training is important to meet individual needs and achieve better results [16]. By establishing models for classification, the differences between data can be evaluated, especially with respect to an individual's response to Achilles tendon vibration. By quantitatively evaluating classification performance metrics, a better understanding of an individual's response to Achilles tendon vibration training can be obtained.

Furthermore, balance control is a complex process involving the coordination of multiple aspects [17]. Among these, the integration of sensory inputs (such as vision and proprioception) and cognitive resources plays a critical role [18], [19], [20], [21]. Through visual perception, individuals gain an understanding of their own posture and the environment, allowing them to make appropriate adjustments to maintain stability. Changes in visual input can affect balance, for example, people's balance can be challenged in low light conditions or when blindfolded [9]. In addition, people often engage in multiple cognitive tasks simultaneously while maintaining balance. For example, they may be talking, problem solving, or performing other cognitive tasks while walking. These cognitive tasks require additional cognitive resources and attention, which may interfere with balance control [22]. These factors may lead to variations in Achilles tendon vibration data under different conditions of the standing balance task. Therefore, when classifying Achilles tendon vibration data, it is necessary to consider different visual and cognitive task states and observe the corresponding data patterns. By increasing the diversity of the data set, a more comprehensive and accurate analysis can be achieved, providing valuable insights for Achilles tendon vibration training and evaluation.

In addition to data acquisition, feature extraction and selection are crucial aspects in building machine learning models [23], [24]. Compared to traditional time-domain or frequency-domain feature extraction methods, wavelet analysis as a signal processing technique can provide more comprehensive information [25]. Wavelet decomposition decomposes data into multiple frequency bands, with each band representing a different frequency range [25], [26], [27]. By performing decomposition and reconstruction operations, features associated with different frequency bands can be extracted. Subsequently, feature selection techniques can be used to identify key features for the classification task of Achilles tendon vibration data. A commonly used feature selection technique is the Genetic Algorithm (GA), which simulates the natural selection mechanism in biological evolution and iteratively selects the optimal feature subset over generations [23]. In the analysis of Achilles tendon vibration and non-vibration data, GA can be combined with machine learning approaches to optimize the selection of feature subsets based on predetermined fitness functions and selection strategies, with the goal of improving the accuracy and performance of the classification models. Different machine learning models may have different perspectives on the importance of features [28]. By combining genetic algorithm with multiple machine learning models such as support vector machine (SVM), logistic regression (LR), and lightweight gradient boosting machine (LGBM), features that contribute significantly to multiple models can be identified. Compared to deep learning models, these learning algorithms preserve the interpretability of the original input features when selecting important features [23], [29]. This allows for a better understanding of the model's decision-making process and the role of key features, thereby improving the interpretability and reliability of classification results.

Based on the above background, this study aims to propose a genetic algorithm-machine learning approach to evaluate Achilles tendon vibration training using wavelet decomposition. Specifically, this study uses wavelet decomposition to extract features and combines genetic algorithm with three machine learning models, namely Support Vector Machine (SVM), Logistic Regression (LR), and Lightweight Gradient Boosting Machine (LGBM), to achieve the classification of Achilles tendon vibration and non-vibration data under different posture conditions and the selection of key features.Through this method, it is possible to extract features from balance data more comprehensively, enhancing the accuracy and interpretability of classifying Achilles tendon vibration training data. This provides new technical support for the development of personalized training programs, offering significant theoretical and practical value.

II. METHOD

A. PARTICIPANTS

This study recruited 40 healthy young adults (age: 24.7 ± 2.7 years, height: 169.5 ± 9.1 cm, weight: 65.7 ± 14.3 kg) to participate in the experiment. Participants had no neurological disorders, lower limb injuries, language, hearing, or visual impairments (normal corrected vision was considered within the screening range). This study was approved by the ethical standards of the Soonchunhyang University of Korea (1040875-202302-SB-015).

B. EXPERIMENTAL EQUIPMENT

To obtain plantar pressure center data, a force plate (Tekscan Inc., 307 West First Street, South Boston, MA 02127, USA) was used to collect data at a sampling rate of 100 Hz. A vibration motor (5V, 80Hz) was used to apply vibration to the Achilles tendon and was encapsulated in a flat plastic cylinder and fixed to both sides of the Achilles tendon with a strap.

C. EXPERIMENTAL PROCEDURE

The participants stood barefoot on a force plate with their hands naturally hanging by their sides, maintaining an upright posture, while COP data was measured under different conditions. The experiment consisted of two conditions: with Achilles tendon vibration and without Achilles tendon vibration. Under the Achilles tendon vibration condition, a vibrating motor was attached to both sides of the participants' Achilles tendons, applying vibrations at a frequency of 80 Hz [6]. Under the no Achilles tendon vibration condition, participants did not receive any additional stimulation. Additionally, visual and cognitive conditions were introduced as covariates. The visual conditions included eyes open and eyes closed. In the eyes open condition, participants were instructed to fixate on a black dot located 2 meters in front of them. Under the cognitive condition, a pre-recorded arithmetic task involving two-digit subtraction or addition problems was played on a mobile phone, and participants verbally calculated the answers. In the non-verbal cognitive condition, no cognitive task was performed.

Experiment in this study was comprised of the following 8 conditions:

1) Eyes open only (Eo)
2) Eyes closed only (Ec)
3) Eyes open, with Cognitive task, without Achilles tendon vibration (EoC)
4) Eyes closed, with Cognitive task, without Achilles tendon vibration (EcC)
5) Eyes open, without Cognitive task, with Achilles tendon vibration (EoV)
6) Eyes closed, without Cognitive task, with Achilles tendon vibration (EcV)
7) Eyes open, with Cognitive task, with Achilles tendon vibration (EoCV)
8) Eyes closed, with Cognitive task, with Achilles tendon vibration (EcCV)

Each task lasted 60 seconds, with a total of 8 tasks performed in a randomized order. Tasks involving Achilles tendon vibration were followed by a 5-minute rest period to minimize the effects of vibration. Tasks without Achilles tendon vibration were followed by a 1-minute rest period before beginning the next task. The completion of 8 tasks constituted a complete experiment. The full experiment was performed twice, with a one-week interval between the two sessions (Figure 1).

D. DATA PREPROCESSING AND FEATURE EXTRACTION

1) DATA PREPROCESSING

In this study, employed a force platform to collect COP velocity data at a frequency of 100 Hz for a duration of 60 seconds. A total of 80 60-second data sets were collected for each condition. To ensure data integrity, unstable segments from the first and last 5 seconds of each data set were excluded. The collected data were then pre-processed by applying a second-order Butterworth low-pass filter with a cutoff frequency of 12.5 Hz. The resulting COP velocity data were used for the subsequent classification analysis to distinguish between Achilles tendon vibration and non-Achilles tendon vibration conditions.

A sliding window approach was used to facilitate the classification process. This approach involved segmenting the data into overlapping windows, each 20 seconds in length, with a step size of 15 seconds. Consequently, this procedure

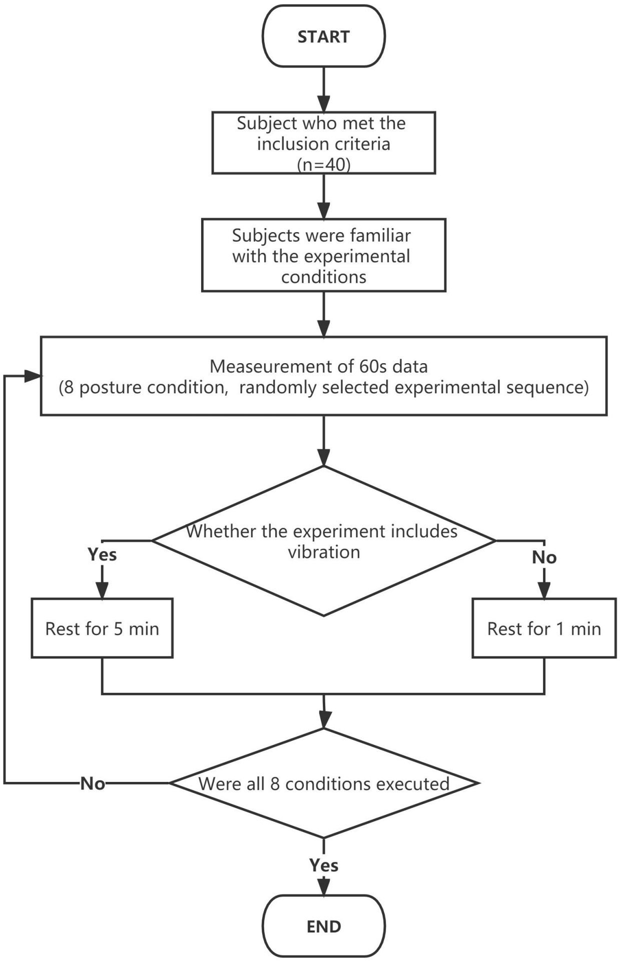

FIGURE 1. Experiment flow chart.

generated a total of 240 samples for each condition, ensuring comprehensive coverage and representation of the data set.

2) WAVELET FEATURE EXTRACTION

Discrete wavelet decomposition can divide a signal into multiple sub-band signals. For a discrete signal, a single round of discrete wavelet decomposition results in two sub-band signals: a low-frequency sub-band (approximation) and a high-frequency sub-band (detail). The low-frequency sub-band contains most of the low-frequency information of the signal, while the high-frequency sub-band contains the high-frequency and detailed information. The process of decomposing the low-frequency sub-band can be repeated to obtain more low-frequency and high-frequency sub-bands until the desired level of decomposition is achieved.

In this study, a 9-level Symlet-8 discrete wavelet decomposition was applied to the original COP velocity signal, resulting in 10 different sub-signals, which were then reconstructed into five distinct frequency bands:

1) high-frequency: 12.50-50.00 Hz (undefined)
2) mid-frequency: 1.56-6.25 Hz (muscle proprioception)
3) low-frequency: 0.39-1.25 Hz (cerebellar)
4) sub- low frequency: 0.10-0.39 Hz (vestibular)
5) ultra-low frequency: below 0.10 Hz (visual)

In addition to an undefined high-frequency range, these frequency bands sequentially represent variations in muscle proprioception, cerebellar function, vestibular system, and visual system [26].

For each of the reconstructed five frequency bands, energy features, amplitude features, entropy features, phase features, and frequency features of the wavelet coefficients were extracted (Table 1).

TABLE 1. Features used in this study.

Feature type	Feature name	Descriptions
Energy	Energy	The sum of the squared amplitudes of a signal over a given time interval, describing the intensity or magnitude of the signal.
	Energy Ratio	The percentage of energy in a specific frequency band after reconstruction relative to the total energy.
Amplitude	Mean Amplitude	The average amplitude of the subfrequency band within a specific frequency range before reconstruction.
	Maximum Amplitude	The maximum amplitude of the subfrequency band within a specific frequency range before reconstruction.
	Minimum Amplitude	The minimum amplitude of the subfrequency band within a specific frequency range before reconstruction.
Entropy	Entropy	The entropy value of a specific frequency band after reconstruction, used as a measure of the signal's uncertainty.
	Mean Entropy	The average entropy value of the subfrequency band within a specific frequency range before reconstruction.
Frequency	Dominant Frequency	The peak frequency with the highest occurrence within a specific frequency band after reconstruction.
	Mean Dominant Frequency	The average of all dominant frequencies within the subfrequency band of a specific frequency range before reconstruction.
	Maximum Dominant Frequency	The maximum of all dominant frequencies within the subfrequency band of a specific frequency range before reconstruction.
	Minimum Dominant Frequency	The minimum of all dominant frequencies within the subfrequency band of a specific frequency range before reconstruction.
Time domain	Mean Value	The average value of all data points within a specific frequency band after reconstruction.
	Variance	The squared average deviation between data points and their mean within a specific frequency band after reconstruction.
	Peak Value	The maximum value points within a specific frequency band after reconstruction.
	Root Mean Square Value	The root mean square of the sum of squares of all values within a specific frequency band after reconstruction.
	Kurtosis	The steepness of the data distribution within a specific frequency band after reconstruction.
	Skewness	The measure of skewness of the data distribution within a specific frequency band after reconstruction.
	Fractal Dimension	A statistical measure that describes the complexity or roughness of the signal within a specific frequency band after reconstruction.

E. GA-ML MODEL

A genetic algorithm-based machine learning model was used to classify Achilles tendon vibration and non-vibration data. Figure 2 shows the data processing and application of the GA-ML model. The pseudocode of the GA-ML model is shown in Algorithm 1.

Algorithm 1 Genetic Algorithm-Based Machine Learning Approach (GA-ML)

Input:
Data: Original feature set
Genetic algorithm parameters: (aCrossRate: crossover probability; aMutationRate: mutation probability; aLifeCount: population size; aGeneLength: gene length; aFitFun: fitness function)
Output:
SelectedFeatures: The optimal selected feature subset
ClassificationPerformance: Classification Performance Metrics (Accuracy, F1 score, Precision, Recall)
Procedure InitializeGeneticAlgorithm:
  Create Genetic Algorithm object with parameters (aCrossRate, aMutationRate, aLifeCount, aGeneLength, aFitFun)
Procedure RunGeneticAlgorithm(*nGenerations*):
for $i = 1$ **to** *nGenerations* **do**
  Execute next generation in Genetic Algorithm
end for
Procedure EvaluateModelPerformance(*features*):
  Train ML model (LGBM / SVM / LR) using selected features
  Calculate Accuracy, F1 score, Precision, Recall
Return a dictionary with performance metrics
Procedure Main:
  Initialize Genetic Algorithm with specified parameters
  Run Genetic Algorithm for a certain number of generations
  Extract selected features from the best individual in the final generation
  Evaluate model performance using the selected features
  Output SelectedFeatures and ClassificationPerformance

Three ML models (SVM, LGBM, and LR) were combined with GA (SVM-GA, LGBM -GA, LR-GA) for feature selection and classification of tendon vibration and non-tendon vibration data (Figure 2). 70% of the dataset was used for training the GA-ML models, while the remaining 30% of the data was used for model performance evaluation.

In detail, a genetic algorithm was used to select subsets of features for training machine learning models. These subsets were selected from the original features to provide an effective data description. The evaluation of these generated feature subsets included the F1 score as a metric to assess the degree of fitting (adaptation). The F1 score, which combines model precision and recall, is commonly used to evaluate the performance of classification models across different classes and is used in GA-ML to evaluate the effectiveness of feature subsets for classification tasks. Furthermore, the population size was set to 80, the number of iterations was set to 200, the crossover probability was set to 0.7, and the mutation probability was set to 0.1.

For SVM, the penalty coefficient C was set to 1.0, the value of gamma was automatically calculated based on the number of training samples, and the radial basis kernel function was used for data mapping.

For LGBM, 80% of the sub-samples were used for training, the learning rate was set to 0.1, each iteration produced 16 leaf nodes, and the maximum depth was set to 5. Then, 80% of the selected features were used to train each tree, and the L2 regularization coefficient was set to 0.1 to enhance the generalization ability of the model.

For LR, default parameter settings were employed after testing for optimum methods.

As shown in Figure 2, it is necessary to apply the GA-ML model iteratively. For the data of different frequency bands, five feature sets was obtained in the feature extraction step. In order to prevent features from specific frequency bands from being missed during the selection process, the genetic algorithm feature selection was performed on the features of different frequency bands, and five optimal feature sets were obtained. Finally, these five best feature sets were merged and subjected to another round of GA-based feature selection to obtain a more representative feature set.

F. KEY FEATURES

Three GA-ML models were used to classify Achilles tendon vibration data under four different conditions, resulting in a total of 12 feature subsets (3 models * 4 conditions). A feature importance ranking was performed for each subset. To identify key features across conditions and models, further feature selection was performed. For each feature subset, the top 10 most important features were retained, and then the features that appeared in at least two or more of the three feature subsets for each GA-ML model were selected as important features, resulting in three feature sets. Finally, the features that appeared in two or more of these three feature sets (i.e., features that were repeated in all three models) were selected as the key features (Figure 3).

III. RESULTS

A. CLASSIFICATION RESULTS

Combining the use of wavelet decomposition for feature extraction and genetic algorithm for feature selection, the classification performance of Achilles tendon vibration and non-tendon vibration under different conditions is shown in Table 2 and Figure 4. Overall, the SVM, LGBM, and LR models achieved classification accuracies of over 80%.

In the classification task of Ec and EcV, SVM achieved the highest accuracy of 89.59% with an F1 score of 89.36%.

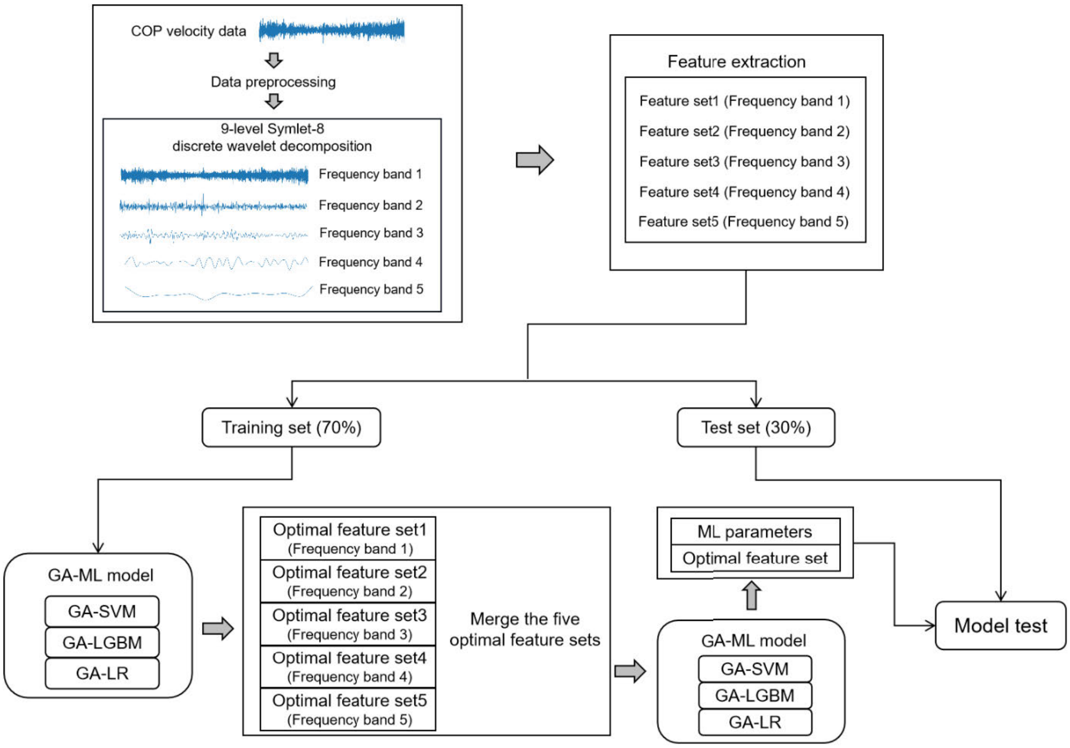

FIGURE 2. Machine learning models combined with genetic algorithms: Frequency band 1(12.50-50.00Hz), frequency band 2(1.56-6.25Hz), frequency band 3(0.39-1.25Hz), frequency band 4(0.10-0.39Hz), frequency band 5(<0.10Hz). GA-SVM is a model combining Support Vector Machine and genetic algorithm; GA-LGBM is a model combining Light Gradient Boosting Machine and genetic algorithm; GA-RL is a model combining Logistic Regression and genetic algorithm.

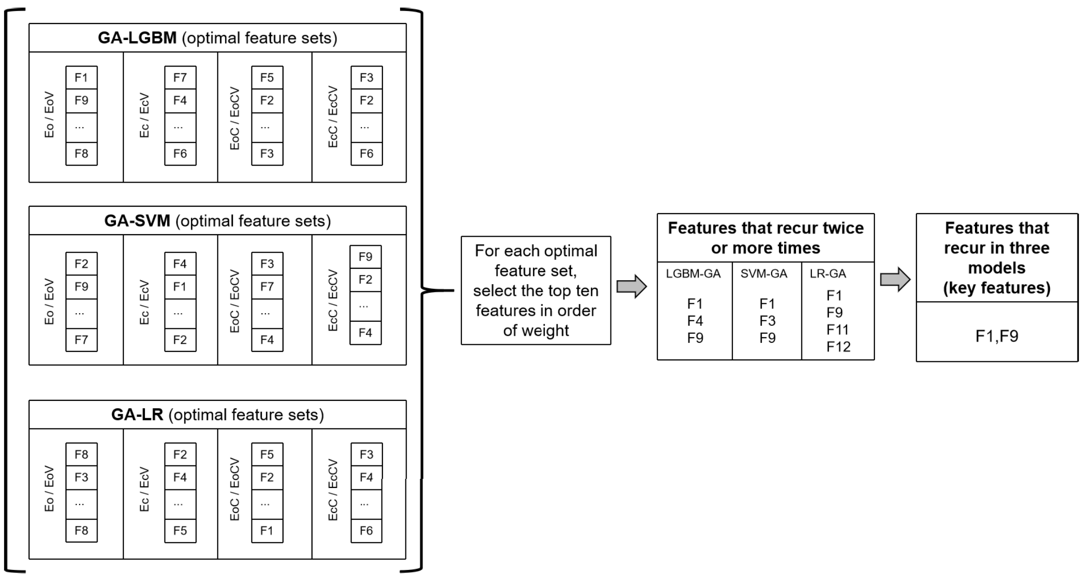

FIGURE 3. Key feature selection method for vibration classification: GA-SVM is a model combining Support Vector Machine and genetic algorithm; GA-LGBM is a model combining Light Gradient Boosting Machine and genetic algorithm; GA-RL is a model combining Logistic Regression and genetic algorithm. Fn represents a different feature example.

It was followed by Logistic Regression with an accuracy of 88.89% and an F1 score of 89.19%. LGBM achieved an accuracy of 87.50% with an F1 score of 87.50%, marking the lowest accuracy of the three models.

In the classification task of Eo and EoV, the highest accuracy was achieved by LGBM with a score of 84.72%, followed closely by SVM and LR, both achieving an accuracy of 84.72% and 83.33% respectively. The corresponding F1

TABLE 2. Classification results.

(a) classification results of GA-SVM

Condition	Accuracy	F1	Precision	Recall
Eo / EoV	84.72	84.29	86.76	81.94
Ec / EcV	89.59	89.36	91.3	87.50
EoC / EoCV	81.25	80.29	84.61	76.39
EcC / EcCV	84.72	84.72	84.72	84.72

(b) classification results of GA-LGBM

Condition	Accuracy	F1	Precision	Recall
Eo / EoV	84.72	84.51	85.71	83.33
Ec / EcV	87.50	87.50	87.50	87.50
EoC / EoCV	81.94	81.94	81.94	81.94
EcC / EcCV	84.03	83.92	84.51	83.33

(c) classification results of GA-LR

Condition	Accuracy	F1	Precision	Recall
Eo / EoV	83.33	82.61	86.36	79.17
Ec / EcV	88.89	89.19	86.84	91.67
EoC / EoCV	82.64	82.52	83.10	81.94
EcC / EcCV	84.03	84.14	83.56	84.72

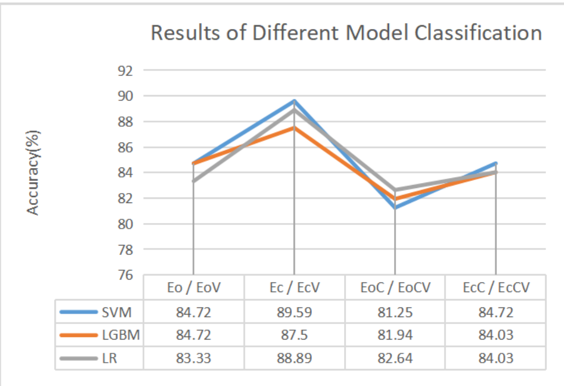

FIGURE 4. The effect of each model on the classification of Achilles tendon vibration and non-vibration data under each condition.

scores were 84.51% for LGBM, 84.29% for SVM, and 82.61% for LR.

In the classification task of EcC and EcCV, the highest accuracy was 84.72% (SVM), while the accuracies of other models were 84.03% (Logistic Regression) and 84.03% (LGBM). The corresponding F1 scores were 84.72% for SVM, 84.14% for LR, and 83.92% for LGBM. In the classification task of EoC and EoCV, the accuracies from highest to lowest were 82.64% (LR), 81.94% (LGBM), and 81.25% (SVM), and the corresponding F1 scores were 82.52% for LR, 81.94% for LGBM, and 80.29% for SVM.

B. KEY FEATURES

The important features selected using the method shown in Figure3 were: Entropy (for the 4th frequency band), Entropy (for the 3rd frequency band), and Mean Entropy (for the 4rd frequency band), Minimum Dominant Frequency (for the 5rd frequency band), as shown in Table 3. Three of these four features are related to entropy. In the comparison of data under conditions with and without tendon vibration, an increase in entropy was observed due to tendon vibration, and these differences were statistically significant ($p<0.05$).

Furthermore, for each classification task, the top 10 features were selected based on their importance ranking, and the frequency of feature usage across different frequency bands is shown in Figure 5. The frequency of feature usage was highest for frequency band F_3 with 29 occurrences, followed by F_5 with 27 occurrences, F_4 with 26 occurrences, F_2 with 23 occurrences and F_1 with 16 occurrences.

TABLE 3. Selected key features.

Key feature	Entropy (3rd band)
	Entropy (4th band)
	Mean Entropy (4th band)
	Minimum Dominant Frequency (5th band)

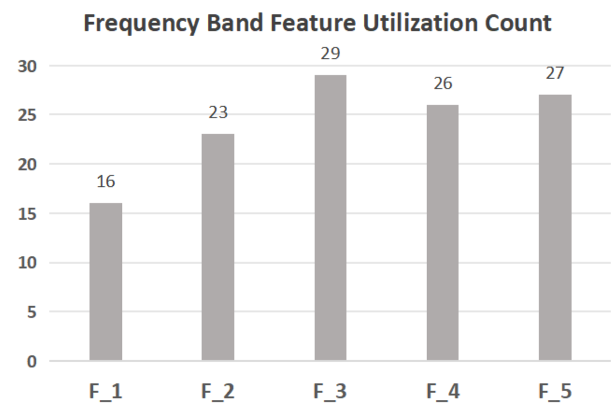

FIGURE 5. The frequency bands' feature utilization frequency. F_1 (undefined): 12.50-50.00 Hz; F_2 (muscle proprioception): 1.56-6.25 Hz; F_3 (cerebellar): 0.39-1.25 Hz; F_4 (vestibular): 0.10-0.39 Hz; F_5 (visual): below 0.10 Hz.

IV. DISCUSSION

The results showed that using a feature set selected through GA, three interpretable machine learning models (SVM, LGBM, LR) achieved classification accuracies of over 80% in the task of differentiating between Achilles tendon vibration and non-vibration data. Specifically, in the absence of cognitive tasks and with eyes closed, SVM demonstrated the highest classification accuracy, reaching up to 89%. Due to the inclusion of healthy young individuals as participants in this study, who have naturally good balance skills, the effect of applying Achilles tendon vibration on balance may be relatively small. As a result, the observed differences in the data may not be as pronounced, resulting in a relatively lower classification accuracy [15]. Metrics such as accuracy can be used to evaluate the effectiveness of Achilles tendon vibration training. Higher classification accuracy indicates a better response to Achilles tendon vibration, which may lead to improved outcomes. Conversely, lower classification accuracy indicates difficulty in distinguishing between vibration and non-vibration data, which may indicate a weaker or less pronounced response to Achilles tendon vibration training. In such cases, appropriate adjustments to training parameters, such as vibration intensity and frequency, or consideration of alternative training methods or additional interventions may be required to increase training effectiveness. In addition, if improvements in balance skills result in changes in data patterns, there may be differences in classification metric results between the pre-training and post-training phases. Future studies could consider integrating changes in classification metrics with other assessment indicators to comprehensively evaluate the effects of Achilles tendon vibration training.

The classification performance varied under different cognitive and visual conditions, indicating potential interactions and modulation among different sensory inputs in balance control. For example, previous research has revealed that in the absence of auditory input, visual and balance sensations become more crucial, implying the existence of interplay and modulation between sensory inputs [30]. The theory of sensory reweighting, as proposed by Rakshatha Kabbaligere et al., further supports the notion that the human body automatically adjusts the weight allocation of different sensory inputs to adapt to environmental changes and maintain stability in balance control [31]. Therefore, the impact of cognitive, visual, and Achilles tendon vibration factors on balance may not simply be additive, and the interrelationships among these three factors require further investigation.

The key feature selection method used in this study considers both the importance of features and the generalization ability of multiple models, resulting in the identification of key features based on their importance and frequency of occurrence across the three models. Among the final selected features, three of them belong to the entropy category, indicating the higher importance of entropy in this classification task. Additionally, it was observed that the entropy under tendon vibration conditions was higher than that under non-vibration conditions in all five frequency bands, and there were significant differences, consistent with the findings of Dettmer et al. [32]. Previous studies have reported that the entropy of the postural control system increases in healthy young individuals during complex balance tasks, indicating more flexible and adaptive postural control [33]. During the process of standing, maintaining stable balance is essential, and an increase in entropy may indicate system disruption and instability, prompting the body to continually adjust posture to restore balance [34]. Therefore, entropy can serve as a biomechanical indicator to evaluate human balance control and help understand the balance control capabilities under different states.

When classifying Achilles tendon vibration data and non-Achilles tendon vibration data, different frequency bands play different roles. Specifically, features within the 0.39-1.25 Hz frequency band (associated with the cerebellum) show the highest frequency of use, followed by those below 0.10 Hz (associated with vision) and the 0.10-0.39 Hz band (associated with the vestibular system). This finding is consistent with previous studies. For example, Morton et al. investigated the mechanisms by which the cerebellum controls balance and movement. As an integral part of the central nervous system, the cerebellum plays a critical role in coordinating movement, regulating posture, and maintaining balance [35]. In addition, the visual and vestibular systems have been identified as significant factors in balance control [36], [37], [38], with their corresponding frequency band features showing higher importance in classification. However, features within lower frequency bands, such as 12.50-50.00 Hz (undefined), show less importance in classification. This may suggest that features within higher frequency bands contribute less to distinguishing Achilles tendon vibration data from non-Achilles tendon vibration data.

These findings provide a foundation for future research aimed at applying machine learning (ML) to Achilles tendon vibration rehabilitation training. However, due to the specific population and experimental conditions examined in this study, further research is warranted to include individuals of different ages, health conditions, and training protocols to obtain more comprehensive and accurate results. Furthermore, further research and understanding of the key features selected in this study will contribute to a deeper understanding of the mechanisms and influencing factors involved in balance control, thus providing a more practical theoretical basis for future balance training and rehabilitation interventions.

In future work, the optimization of the model is of paramount importance. First, increasing the size of the dataset is imperative to improve the generalization performance of the model. In addition, it is crucial to consider employing more sophisticated machine learning models to better capture the intricate relationships within the data. Regarding feature selection, more refined and context-adaptive approaches should be explored to ensure that the selected features accurately reflect the influence of visual conditions or cognitive tasks. Therefore, future work should not only focus on improving the overall model performance, but also on exploring the key features that enable the classification of data under visual conditions or cognitive tasks, thus providing deeper insights for further understanding in the field of balance control.

V. CONCLUSION

This study used machine learning techniques, the classification of Achilles tendon vibration and non-vibration data was achieved and the key features for this classification task were identified. In addition, additional experiments validated the proposed method for its ability to identify COP attributes associated with two other conditions (visual / cognitive tasks).

These research findings provide a theoretical foundation and methodological support for future studies related to Achilles tendon vibration rehabilitation training.

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