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Molecular & Cellular Biomechanics 2025, 22(2), 1156.
https://doi.org/10.62617/mcb1156

Article

Application of quantitative analysis of biomechanical data in predicting healthcare investment trends

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CITATION

Jiao Z, Li S. Application of quantitative analysis of biomechanical data in predicting healthcare investment trends. Molecular & Cellular Biomechanics. 2025; 22(2): 1156. https://doi.org/10.62617/mcb1156

ARTICLE INFO

Received: 18 December 2024
Accepted: 9 January 2025
Available online: 21 January 2025

Abstract: Traditional methods for predicting investment trends often rely on macroeconomic data, overlooking the influence of individual biomechanical characteristics on decision-making, particularly in the health and medical fields. This paper seeks to enhance the accuracy of healthcare investment trend predictions by integrating high-precision biomechanical data acquisition technology with advanced quantitative analysis methods. High-precision sensors and smart wearable devices are employed to collect individual biomechanical data, encompassing dynamic features such as sports performance, joint angles, and gait. To ensure data quality, a rigorous preprocessing procedure is implemented. Principal component analysis (PCA) is utilized for feature extraction, minimizing redundant information and isolating the most representative biomechanical features. During the data analysis phase, a hybrid model combining random forests and support vector machines (SVM) is employed to predict healthcare investment trends. Random forests are applied for feature selection and regression analysis, while SVMs address classification tasks for trend prediction. The results indicate that the proposed model achieves an accuracy and precision exceeding 0.9, with healthcare investment returns on investment (ROI) ranging from 20% to 50%. The findings underscore the potential of biomechanical data in providing valuable insights for healthcare investment trend predictions, ultimately driving innovation and progress in the industry.

Keywords: biomechanical data; quantitative analysis; machine learning; investment prediction; time series

1. Introduction

With the aging of the global population and increasing awareness of health, the medical and healthcare industry is experiencing unprecedented growth opportunities [1,2]. However, as technology continues to advance, investment trends in this field have become increasingly intricate, particularly with the incorporation of biomechanics and health data [3,4]. Biomechanics, which focuses on human movement and mechanical behavior, has made notable strides in areas such as sports medicine, rehabilitation therapy, and personalized health management [5,6]. The rapid development of smart wearable devices and sensor technology has led to the accumulation of vast amounts of biomechanical data. Yet, traditional analytical methods face significant limitations, especially in terms of data collection precision, analytical depth, and interdisciplinary integration [7,8]. Consequently, effectively utilizing this data to predict trends in healthcare investment has emerged as a critical challenge.

Recent years have witnessed growing scholarly interest in applying biomechanical data to health management and medical fields [9,10]. For instance, some researchers analyze athletes' biomechanical data to evaluate sports performance and predict injury risks [11,12], while others predict fall risks among the elderly using biomechanical analysis combined with smart devices [13,14]. However, despite these initial achievements, several limitations remain evident [15,16]. First, existing studies often rely on conventional data collection methods, constrained by the capabilities of limited sensors and analysis tools, thereby failing to comprehensively capture the complex biomechanical characteristics of the human body [17,18]. Second, many studies focus on individual-level health interventions without addressing broader cross-industry trends or large-scale market demands [19,20]. As a result, traditional research in the application of biomechanical data to healthcare investments suffers from inadequate accuracy, simplified analytical frameworks, and insufficient support for predicting future trends [21,22].

To address these challenges, researchers have increasingly turned to advanced quantitative analysis methods, such as machine learning and big data analytics, to enhance the accuracy and depth of biomechanical data analysis [23,24]. For example, deep learning algorithms have been used for real-time analysis of athletes' biomechanical data, significantly improving injury prediction accuracy [25,26]. Similarly, regression analysis and time series forecasting have been employed to combine multi-source biomechanical data with patient health histories, enabling predictions of rehabilitation progress and treatment needs [27,28]. While these methods have improved analytical precision, they still fall short in establishing comprehensive correlations between biomechanical data and healthcare investment trends [29,30].

This paper aims to address these gaps by leveraging advanced biomechanical data acquisition technologies and cutting-edge quantitative analysis methods. Specifically, it proposes a framework that integrates high-precision biomechanical data collection with machine learning and big data analytics to analyze the biomechanical characteristics of diverse populations (e.g., athletes, the elderly) and predict their needs in health management and rehabilitation. The study further connects these insights with investment trends in the medical and healthcare industry. Through this approach, the study aspires to provide investors with more accurate predictions of healthcare trends, thereby fostering innovation and driving development in the industry.

By solving the challenges of data accuracy, analytical depth, and interdisciplinary integration in traditional research, this paper aims to establish a novel framework that bridges biomechanical data analysis and healthcare investment decisions, ultimately contributing to the sustainable growth of the medical and healthcare industry.

2. Biomechanical data acquisition

2.1. Application of motion sensors

Inertial measurement units are a combination of accelerometers, gyroscopes and magnetometers to achieve real-time monitoring of the three-dimensional acceleration, angular velocity and direction of the human body during movement. In this study, IMU (Inertial Measurement Unit) is mainly used to monitor the dynamic characteristics of individual movement patterns, gait cycles, stride length, and step frequency. The advantages of IMU are its high accuracy, low latency and ability to collect data in real-time, which is essential for capturing rapidly changing motion processes. By fixing the IMU sensor on the ankle, waist or shoulder of an individual, it is possible to obtain all-round data during the movement process, thereby analyzing key indicators such as the intensity of each step, gait asymmetry, and changes in joint movement angles.

During the data acquisition process, the accuracy of the IMU sensor is solved by regular calibration and multi-sensor fusion algorithms. By using the Kalman filter algorithm for sensor data fusion, the accuracy and stability of the data are further improved, and the measurement error of a single sensor is reduced. Especially during rapid turns or intense movements, the IMU can provide accurate dynamic feedback.

2.2. Application of force plates

To obtain data related to body load, this paper uses force plates in the experiment. The force plate can accurately measure the vertical force applied by an individual in standing, walking, running, and other motion states, as well as the resulting dynamic changes. The vertical impact force and ground reaction force measured by the force plate can further analyze the individual's muscle load and joint stress. The force plate captures the instantaneous force changes each time the sole of the foot contacts the ground through high-frequency sampling, and records the impact of landing, standing stability, and the force distribution of gait. Especially in rehabilitation medicine and sports injury assessment, the data provided by the force plate can help doctors evaluate the force on joints and bones during exercise, and thus provide a basis for personalized treatment plans.

To overcome the challenge of low accuracy of the force plate in dynamic movement, this study adopted a combination of force plate and IMU data. By synchronizing the time and aligning the data of the two in space, more comprehensive biomechanical data can be obtained, making gait analysis and load monitoring more accurate. The specific method is to fuse the vertical force data of the force plate with the angular velocity data of the IMU through a complementary filtering algorithm, thereby eliminating the error of the force plate in the dynamic process.

2.3. Application of smart wearable devices

In addition to motion sensors and force plates, wearable devices such as smart bracelets and smart insoles are also used to collect biomechanical data. The advantages of these devices are their convenience of wearing, feasibility of long-term use, and support for real-time health monitoring. Smart bracelets can monitor individual physiological status data such as heart rate, cadence, and sleep quality. Smart insoles monitor gait and stride in real-time through built-in pressure sensors, and can effectively capture details such as the pressure distribution of the sole of the foot and the dynamic changes of the sole of the foot at each step. The data collection of smart bracelets uses photoelectric volume pulse wave sensing technology to monitor heart rate, current sensing technology to monitor gait, and combined with built-in accelerometers to analyze movement parameters such as cadence and stride. Smart insoles measure the pressure changes of the foot in contact with the ground through pressure sensor distribution, and then analyze important indicators such as the center of gravity distribution and plantar support force of the individual when walking and running.

The data advantage of these devices is that they can provide real-time monitoring, and the data transmission is convenient, which can achieve long-term tracking. Through the wireless sensor network, all collected data can be uploaded to the cloud platform in real-time for further analysis. In sports medicine and health management, the popularity of smart devices makes it possible to dynamically monitor the health status of individuals, especially in long-term monitoring and personalized health management. It has great application potential.

2.4. Data synchronization and fusion

To effectively integrate the data of various sensors, this study adopted data synchronization and fusion technology. Since the timestamps and sampling frequencies of data collected by different devices may be different, the data must be synchronized. This paper uses timestamp alignment technology to time align data with different sampling rates through interpolation methods, thereby ensuring the consistency of data from all sensors in the time dimension. In addition, a weighted fusion algorithm is used to integrate the measurement results of different devices in order to provide more comprehensive and accurate biomechanical parameters in the data analysis stage.

Table 1 records the biomechanical data collected at intervals of 1 min, covering the key parameters of individuals during exercise.

Table 1. Acquisition of motion parameters.

Time Interval (min)	Gait Cycle (s)	Step Length (m)	Step Frequency (steps/min)	Joint Angle (°)	Heart Rate (bpm)
0	1.2	0.75	100	45	72
1	1.1	0.74	105	46	75
2	1.3	0.76	98	44	78
3	1.1	0.72	110	47	80
4	1.2	0.73	102	45	76
5	1.4	0.78	95	48	82
6	1.1	0.75	108	46	74
7	1.3	0.77	99	44	77

In the data fusion process, Kalman filtering and complementary filtering algorithms are used. The former is used to process the dynamic data of IMU and force plate, and the latter is mainly used to combine the physiological data of the smart bracelet and insole. Kalman filter can effectively suppress noise, optimize sensor measurement error, and provide more accurate dynamic motion analysis results, while complementary filtering effectively fuses low-frequency IMU data and high-frequency force plate data to ensure the timeliness and accuracy of data.

3. Data preprocessing and cleaning

3.1. Outlier detection and denoising

Outliers are extreme values in the data that deviate from the normal range, which may be caused by sensor failure or environmental interference. This paper uses outlier detection based on statistical methods to identify and eliminate unreasonable data points. The specific steps are as follows:

For each biomechanical indicator (such as gait cycle, stride, joint angle, etc.), first calculate its mean and standard deviation in the entire data set. Assuming that the data follows a normal distribution, when a data point exceeds the mean ±3 times the standard deviation, the point is considered an outlier. For these outliers, choose to remove them or replace them with neighboring data. Based on the box plot method, the quartiles (Q1, Q3) and interquartile range (IQR = Q3−Q1) of each variable are calculated, and the outliers are defined as values less than Q1−1.5IQR or greater than Q3 + 1.5IQR. This method helps to identify relatively outlier data points and avoid the influence of extreme data points on the results of subsequent analysis. Through the above method, this paper effectively identifies and removes noise in the data and improves the accuracy of the data set.

In the original data of **Figure 1**, the outliers are widely distributed, and the extreme outliers have a significant impact on the distribution of the data. After removing the outliers, the volatility and discreteness of the data are effectively reduced, and the distribution of the data is more concentrated and stable. After removing the outliers, the data is more representative and suitable for further analysis.

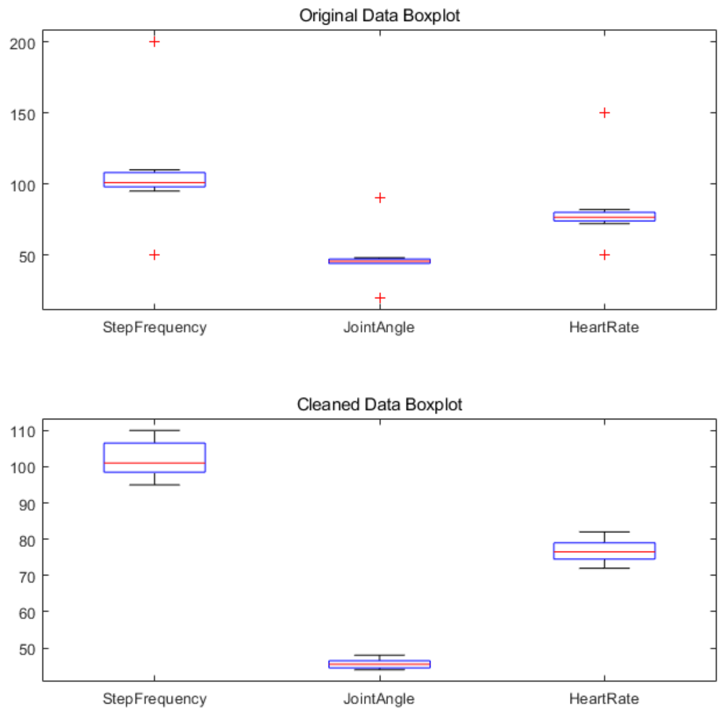

Figure 1. Outlier detection and denoising.

3.2. Missing value filling

Due to sensor failure or environmental factors, the collected biomechanical data often have missing values. The existence of missing data will lead to deviations in the analysis results, so it must be filled. This study used linear interpolation to fill in the missing values in the data. The specific process is as follows:

For each variable containing missing values, the data is first sorted in chronological order to ensure the temporal nature of the data. For the case where the missing value is between two known data points, the linear interpolation method is used to fill it. For multiple missing data points, the method of multiple interpolation before and after is used for recursive filling to ensure that the filled data can be consistent with other data points. Using linear interpolation to fill missing values can retain the temporal nature and trend of the data to the greatest extent, avoiding the reduction of sample size or distortion of analysis results due to the direct deletion of missing data.

3.3. Data standardization

Since different types of biomechanical data (such as gait analysis, muscle load, joint angle, etc.) may have different dimensions (for example, the unit of angle is degree and the unit of load is Newton), the z-score standardization method is used to process the data during data analysis. The standardized data can effectively eliminate the dimensional differences between different features, avoid the excessive influence of some features with larger dimensions on the analysis results, and improve the stability and reliability of the subsequent analysis model.

4. Feature extraction and selection

4.1. Feature extraction

First, based on multiple variables in biomechanical data, this paper extracts several core features that can effectively reflect the individual's sports performance and health status.

The moment when the foot contacts the ground is captured by the IMU sensor, and the duration of a complete gait cycle is calculated, that is, the time interval from one foot landing to the same foot landing again. The gait cycle reflects the individual's movement frequency and is usually used to analyze the stability and movement efficiency of the gait. Stride refers to the horizontal distance between the feet in each step, and the step frequency is the number of steps per unit time. Through the acceleration data of the IMU sensor and the pressure data of the force plate, this paper can accurately calculate the stride length and step frequency. These two features are important indicators for analyzing individual gait and exercise intensity. The IMU sensor is used to measure the bending angle of the joints during exercise, especially the angle changes of the knee and ankle joints. This feature is crucial for assessing the risk of sports injuries, exercise ability, and joint function. The electrical activity of the muscle is monitored by the electromyographic sensor, reflecting the activity of the muscle during exercise. Changes in muscle activity can be used to assess exercise load and fatigue. By analyzing the symmetry of the gait of both legs (including differences in step length, step frequency, landing time, etc.), the asymmetry during movement can be evaluated, which is of great significance for evaluating gait abnormalities, sports injuries, and rehabilitation.

These features are obtained through precise calculations by combining motion sensors (including IMU and force plates), electromyography sensors, and smart wearable devices (including insoles and bracelets), providing basic data for subsequent feature selection and trend prediction.

4.2. Feature selection and dimensionality reduction

There may be a large number of redundant features in biomechanical data, which will affect the efficiency and accuracy of the analysis. Therefore, feature selection and dimensionality reduction are key links to improve model performance.

To solve the problem of feature redundancy, this study used the principal component analysis method to reduce the dimensionality of the extracted features. PCA (Principal Component Analysis) is a linear transformation method that extracts new features with the largest variance in the data by calculating the covariance matrix between features. These new features are called principal components. Principal components can effectively retain the main information in the data while removing unnecessary redundant features.

The specific steps of PCA are as follows: First, all biomechanical features are z-score standardized to ensure that features of different dimensions are processed under the same standard. The standardized data has zero mean and unit standard deviation, eliminating the deviation caused by different dimensions. According to the standardized feature data, the covariance matrix between them is calculated. The covariance matrix reflects the linear relationship between features. The larger the covariance value, the stronger the correlation. Through eigenvalue decomposition, the eigenvalues and corresponding eigenvectors of the covariance matrix are obtained. The larger the eigenvalue, the larger the proportion of the corresponding eigenvector in the data variance. According to the size of the eigenvalue, the first few principal components are selected, usually the first n principal components with the most explained variance. The selected principal components can retain more than 95% of the information in the original features. Finally, the original data is projected onto these principal components to obtain the reduced dimensionality data set. In this way, this paper compresses the high-dimensional feature space into a low-dimensional space while retaining the most representative information. In addition to PCA, this paper also uses feature selection methods based on tree models, such as random forests. By training a random forest model, this paper can obtain the importance score of each feature and select the features that contribute most to the prediction task. The random forest model uses the ensemble learning idea of multiple decision trees to effectively screen out features that have a greater impact on the prediction results by calculating the “split importance” of each feature in each tree.

Figure 2 shows the correlation coefficients between different biomechanical features. The horizontal and vertical axes represent different features, and the cells represent the correlation between the two features. The correlation value between cadence and gait cycle is above 0.9, indicating that there is a strong positive correlation between the two features and high redundancy. We choose to retain cadence and remove gait cycle to avoid redundant data affecting model performance.

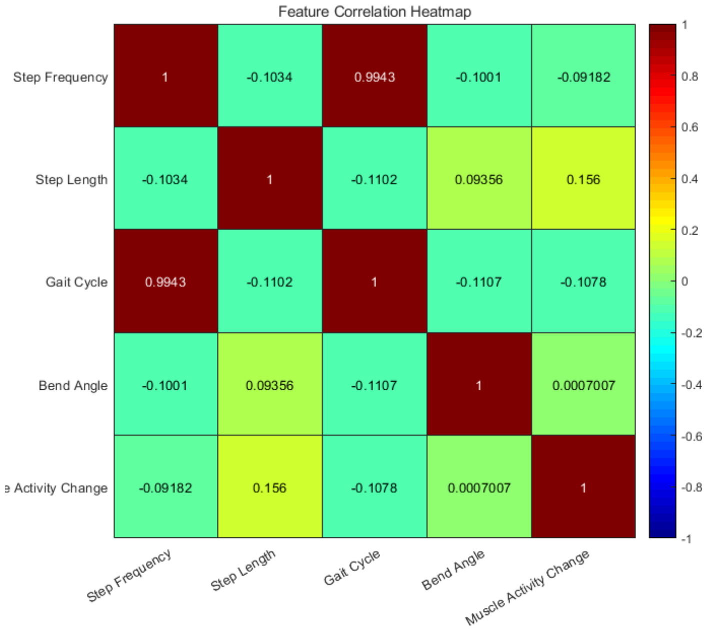

Figure 2. Feature correlation.

5. Trend prediction model construction

5.1. Data preparation and feature fusion

In trend prediction, this paper combines two types of data: biomechanical data and market data in the medical and health fields. Biomechanical data comes from smart wearable devices and motion sensors, mainly including gait, joint angle, stride, and other features, reflecting individual health status and sports performance; while market data includes investment trends, market demand, policy changes, etc., in the medical and health industry, reflecting the overall development dynamics of the industry. This paper fuses these two types of data. Specifically, this paper uses the features of biomechanical data as input features, and the trend changes of medical and health market data as target variables. These features and target variables are integrated into a unified data set for training and testing trend prediction models.

5.2. Random forest model construction

Random forest models are widely used in feature selection and regression tasks of large-scale data sets. In this study, random forests are used to process large-scale biomechanical data and market data to predict investment trends in the healthcare field. First, this paper uses random forests for feature selection. By training a random forest model containing multiple decision trees, the contribution of each input feature to the prediction result can be evaluated. By calculating the "split importance" of each feature in each tree, the most representative features for predicting healthcare investment trends are screened out. Features with low importance scores are eliminated, reducing redundant information and improving the training efficiency of the model.

Another important application of random forests is regression problems. This paper regards the prediction task of healthcare investment trends as a regression problem. By training a regression model, random forests can accurately predict the future trend of market investment through the integrated results of multiple decision trees. By integrating the results of multiple trees, the model avoids the overfitting problem that may occur in a single model and improves the robustness of the prediction. During the training process, the random forest model is hyperparameter tuned, mainly including parameters such as the number of trees (n_estimators) and the maximum depth (max_depth). This paper uses the cross-validation method to evaluate the performance of the model and ensure its generalization ability.

The horizontal axis of **Figure 3** represents the number of model iterations during the training process, and the vertical axis represents the accuracy of the model after each training iteration. As the number of training times increases, the accuracy of the model gradually increases. Adjusting different hyperparameters (such as the number and depth of decision trees) can affect the learning efficiency, learning speed, and final accuracy of the model.

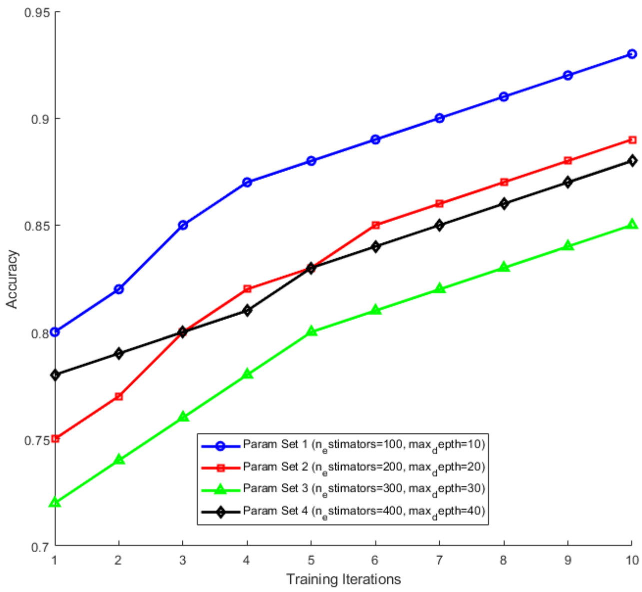

Figure 3. Training process.

5.3. Support vector machine model construction

Unlike the regression model of random forest, support vector machine is mainly used for classification tasks. In this study, this paper uses SVM (Support Vector Machine) to build a classification model for medical and health investment trends. By analyzing biomechanical data and market data in different time periods, the direction of future market trends (such as rising, falling or flat) is predicted.

Similar to random forest, this paper standardizes the data and selects features to ensure that SVM can perform effective classification in high-dimensional feature space. In particular, this paper uses RBF (Radial Basis Function) kernel function (radial basis function) to deal with nonlinear problems, because market trends often present complex nonlinear relationships. By selecting appropriate SVM hyperparameters (such as penalty parameter C and kernel function parameter gamma), this paper can train a classification model to predict the investment trend of the future market. SVM accurately classifies by finding an optimal hyperplane to maximize the interval between categories.

5.4. Model fusion

In order to further improve the accuracy of trend prediction, this paper adopts the strategy of model fusion to combine the prediction results of random forest and SVM models. Model fusion can combine the advantages of both and improve prediction performance. In model fusion, this paper integrates the prediction results of random forest and SVM by weighted average. Specifically, this paper assigns different weights according to the performance of the two models. Generally speaking, models with better performance will receive higher weights, which will affect the final prediction results.

6. Evaluation

6.1. Logarithmic loss training

Logarithmic loss is a metric used to evaluate the prediction performance of classification models, especially to measure the difference between the probability distribution of the classification model output and the actual label. It is usually used for binary and multi-classification problems, and is suitable for models with probabilistic output. Select a binary classification problem. The dataset should contain input and output. Divide the dataset into training set and validation set by 70%/30%. Set the training rounds of the model and monitor the changes in Log Loss (Logarithmic Loss) during each training cycle. After each training, the model is used to predict the data in the validation set and output the predicted probability value.

The X-axis in **Figure 4** represents the number of trainings, and the Y-axis represents the value of Log Loss. In the early stages of model training, Log Loss decreases because the model begins to gradually learn the patterns in the data. As the number of trainings increases, Log Loss gradually approaches the optimal value.

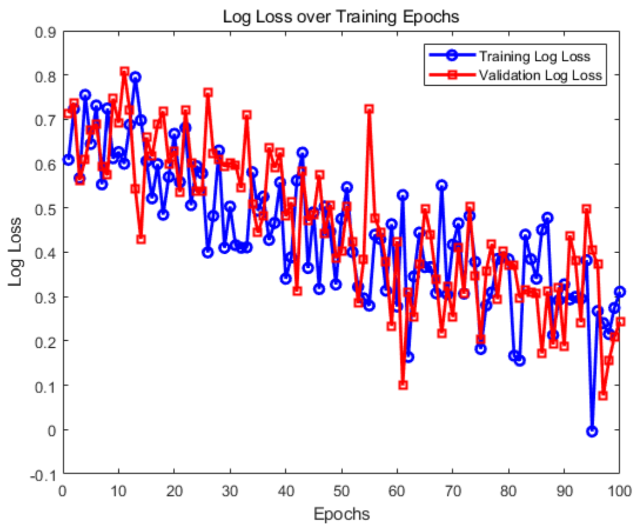

Figure 4. Model training.

The curve begins to rise after a certain stage, and the increase in the number of training rounds leads to an increase in Log Loss, which may be a signal of overfitting. Even if the Log Loss of the training set continues to decrease, the performance of the model on the validation set deteriorates.

6.2. Prediction performance

Prediction performance includes prediction accuracy and precision. Prediction accuracy refers to the consistency between the model's prediction results and the actual results. It is usually used for classification problems and indicates the proportion of correct predictions. Precision refers to the proportion of all instances predicted by the model as positive that are actually positive. The higher the precision, the more accurately the model predicts the positive instances. Compare the performance of the four models in terms of accuracy and precision.

The X-axis in **Figure 5** represents the names of the four models, and the Y-axis shows the accuracy and precision. The fusion model performs well in both accuracy and precision, which are greater than 0.9, and the bars are relatively high, indicating that the fusion model has good performance in both aspects.

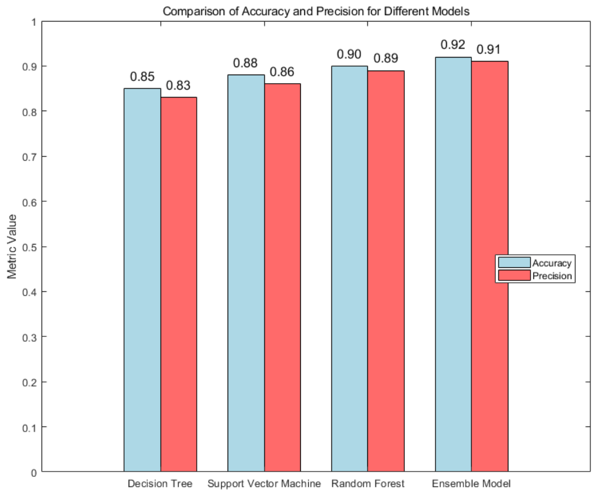

Figure 5. Prediction performance.

6.3. Error assessment

Mean square error is a commonly used evaluation indicator in regression models, which represents the square average of the difference between the predicted value and the true value. The smaller the MSE (Mean Squared Error), the better the prediction effect of the model. The root mean square error represents the error of the model in the regression task. To compare the performance of different regression models in prediction, the mean square errors and root mean square errors are used as evaluation indicators.

Table 2 shows the three experimental errors of different regression models in prediction. The fusion model performs best and has the smallest prediction error, so it is recommended. Random forest also performs very well, with a prediction error second only to the fusion model, and is suitable for most regression tasks. The decision tree performs poorly and may require further optimization to improve its prediction performance.

Table 2. Errors of different models.

Model	MSE (1)	MSE (2)	MSE (3)	RMSE (1)	RMSE (2)	RMSE (3)
Decision Tree	0.045	0.043	0.047	0.213	0.208	0.217
Support Vector Machine	0.038	0.036	0.04	0.195	0.19	0.2
Random Forest	0.022	0.021	0.023	0.148	0.145	0.151
Ensemble Model	0.018	0.017	0.019	0.134	0.13	0.138

6.4. Financial return rate

The financial return rate measures the ratio between the economic benefits generated by an investment and its costs.

Table 3 shows the financial return rate of different healthcare investment projects, which is used to measure the relationship between the return and cost generated by each investment. Through ROI (Return on Investment), investors or decision-makers can evaluate which projects have better economic benefits and which projects have lower returns. See that ROI is between 20% and 50%.

Table 3. Financial return rate.

Investment Project	Investment Cost	Investment Return	Financial Return on Investment
New Medical Equipment Purchase	500,000	600,000	20%
Health Management Project Promotion	200,000	300,000	50%
Elderly Care Center Construction	1,000,000	1,200,000	20%
Medical Informatization Construction	300,000	450,000	50%
Health Education Program	150,000	225,000	50%

7. Conclusions

This paper integrates biomechanical data with market data in the healthcare sector to construct a trend prediction model based on machine learning and time series analysis, achieving accurate predictions of healthcare investment trends. The study begins by collecting individual biomechanical data using high-precision sensors and smart wearable devices, ensuring data quality and representativeness through preprocessing techniques and feature extraction. These refined datasets are then combined with machine learning algorithms, including random forests and support vector machines, to perform regression and classification of investment trends, enhancing the stability and accuracy of long-term investment predictions.

While the proposed model demonstrates promising results in trend prediction, it is not without limitations. The model's training process relies heavily on high-quality data, and its performance may be sensitive to sudden market changes. Future research should explore the incorporation of advanced feature fusion techniques and deep learning methods to further improve prediction accuracy and model adaptability. Additionally, efforts to integrate real-time market dynamics could enhance the robustness of predictions and support intelligent investment decision-making in the healthcare industry.

Author contributions: Conceptualization, ZJ and SL; methodology, ZJ; software, ZJ; validation, ZJ and SL; formal analysis, ZJ; investigation, ZJ; resources, ZJ; data curation, ZJ; writing—original draft preparation, ZJ; writing—review and editing, ZJ; visualization, ZJ; supervision, ZJ; project administration, ZJ; funding acquisition, SL. All authors have read and agreed to the published version of the manuscript.

Ethical approval: Not applicable.

Conflict of interest: The authors declare no conflict of interest.

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