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ORIGINAL

REAL-TIME INJURY RISK ASSESSMENT AND EARLY WARNING FOR SOCCER PLAYERS UTILIZING SENSORS AND MACHINE LEARNING

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ABSTRACT

In modern soccer, player health and injuries are critical to team competitiveness and sustainability. Traditional injury risk assessment methods have limitations, but with the development of sensor technology and machine learning algorithms, new possibilities for real-time injury risk assessment of players are provided. The application of IoT and AI technologies is driving the development of intelligence, and combining them to monitor the physiological state and athletic injurie load of players in real time with the help of wearable sensors can provide objective and accurate data support. Using machine learning algorithms, sensor data can be analyzed to build a prediction model for player injury risk. Individualized injury risk assessment for different players becomes possible. The soccer movement recognition and analysis combine sensor data to design a framework for soccer movement recognition and assessment, in order to achieve real-time monitoring and risk assessment of players during matches and training, and to help minimize the risk of player injuries.

KEYWORDS: Injury Risk Assessment; Sensors; Machine Learning; Early Warning

1. INTRODUCTION

In the modern game of soccer, the health and injuries of athletes are critical to the competitiveness and sustainability of teams. Soccer being a high-intensity sport, soccer players are at risk of injuries that may have long-term effects on their careers and lives. However, traditional injury risk assessment methods are often subjective and limited based on experience and apparent symptoms. With the development of sensor technology and machine learning algorithms, new possibilities for real-time injury risk assessment and early warning for athletes are provided. With the development of the new generation of information technology, the application of IoT and AI technology is becoming more and more widespread (Chen, Han, et al., 2023; Chen, Li, et al., 2023; Li & Cao, 2021). Its application field involves industry, agriculture, transportation and other infrastructure fields, effectively promoting the intelligent development of various industries (Ouyang et al., 2024). In contrast, the current application of IoT technology in the direction of sports competition is still in the primary exploration stage in general. Combining IoT and artificial intelligence technology to realize human-machine and human-network system-human interaction by means of inertial sensor-based motion capture has become an international cutting-edge research hotspot involving a high degree of multidisciplinary crossover and knowledge integration. Through wearable sensors (e.g., accelerometers, gyroscopes, heart rate monitors, etc.), athletes' physiological state, exercise trajectory, and exercise load can be monitored in real time, thus providing more objective and accurate data support. With the help of machine learning algorithms, a large amount of collected sensor data can be analyzed and pattern recognition can be performed to establish a prediction model of the athlete's injury risk. This enables individualized injury risk assessment for different athletes. Human actions are described using feature vectors with time series, and through the transfer of action feature sequences, time series-based algorithms can recognize and analyze daily human actions. Hidden Markov Model (HMM) was used by Zappi et al. for dynamic sensor selection system to realize the recognition of operational actions of assembly workers (Zappi et al., 2008). However, the recognition performance of HMM-based classifiers is largely limited by the assumptions of no posteriority and chi-squaredness, and the Conditional Random Field (CRF) model was used for action recognition of more complex sequences. Belgacem et al. used CRF to recognize human action sequences and compared it with HMM and showed that CRF outperformed HMM (Belgacem et al., 2017). Due to the context-dependent pattern analysis, the recognition algorithm based on time series often has a better classification effect for recognizing complex human actions, but the algorithm model is complex, and the model computing cost is high and difficult to realize real-time recognition when the data volume is large. Static recognition algorithms based on a single example mainly include threshold-based recognition algorithms and recognition algorithms based on artificial intelligence: Hssina et al. used a decision tree algorithm to complete the distinction of common actions (Hssina et al., 2014); K-Nearest Neighbour (KNN) algorithm was used by Bansal et al. for online recognition analysis of human actions (Bansal et al., 2022). SVM is also heavily utilized in related research. In addition to these common algorithms, decision tables, dynamic time regularization, and extreme learning machines are also common algorithms to improve the accuracy of the algorithm. It can be seen that static learning algorithms based on a single example have received the attention of a large number of researchers and achieved good classification results. There is a significant demand and opportunity for the application and development of combining IoT and AI technology in the teaching, training, and competitions of soccer. The recognition and analysis of soccer sports movement primarily focuses on the calves and ankles of athletes. This involves using wearable devices with built-in inertial sensors that are attached to the ankle. Machine learning algorithms are then employed to identify the specific movements and estimate their intensity. In general, inertial sensors have limited sensitivity when it comes to capturing data related to lower body movements in sports, particularly in soccer. This is due to the complexity of the movements involved and the individual differences among athletes. Additionally, existing algorithmic models for recognizing human activity in research are not easily applicable to recognizing soccer movements directly. Traditional soccer teaching and training techniques have limited utilization of wearable sensing devices for collecting and analyzing real-time data. Additionally, there is a deficiency in capturing human movement and recognizing gestures based on sports science ideas. The existing model lacks the capability to thoroughly examine the intricate and noisy stream of action data. In this paper, the method of soccer action data analysis based on sensor data is investigated, and based on the shortcomings of the existing related research and the needs of practical application scenarios, a framework for soccer action recognition and assessment is designed, which uses wearable devices to collect soccer action data and constructs a machine learning algorithm model to recognize, assess, and analyze the intensity of the movement of soccer action. In order to achieve real-time monitoring and risk assessment of athletes during games and training, and to help coaches and medical teams make timely interventions to minimize the risk of injuries to athletes and improve their health and competitive performance.

2. System Design and Data Acquisition

Wearable sensors have found extensive use in sports recognition, however, the current methods for applying them are not suitable for recognizing soccer movements (Nunes Rodrigues et al., 2020). Additionally, the limited number of coaches available make it challenging to accurately assess the individual performance of each soccer player using precise data quantification. Initially, we present an IoT-based system for recognizing soccer movement. This system is capable of visually displaying the specific type of movement and the level of expertise in performing the movement on mobile devices. This section provides comprehensive information on the hardware design, interface software, and data gathering procedure, including particular details for each phase. Figure 1 depicts the structure of the system, comprising a wireless wearable device, a mobile device, and a cloud-based data processing platform.

The motion sensor is attached to the soccer player's right ankle in the IoT system. The motion data is transferred wirelessly via Bluetooth technology to the cloud platform for additional analysis and computation (Piñeiro-Cossio et al., 2021).

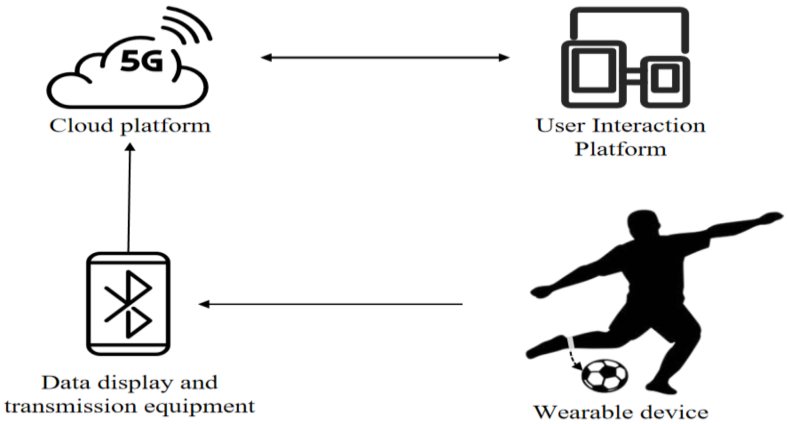


Figure 1: Flowchart of the platform.

The low-power Bluetooth device transmits exercise data collected by the wearable device to the mobile device through the IoT system. Once the mobile device receives the exercise data, it uses cloud computing technology to send the raw data to the remote service platform for data collection and processing. The platform allows the user to view the analysis results of their exercise performance.

2.1 Hardware and Software System Design

The Soccer Motion Recognition and Evaluation System begins by collecting data using a wireless wearable device. Figure 2 illustrates the components of the device.

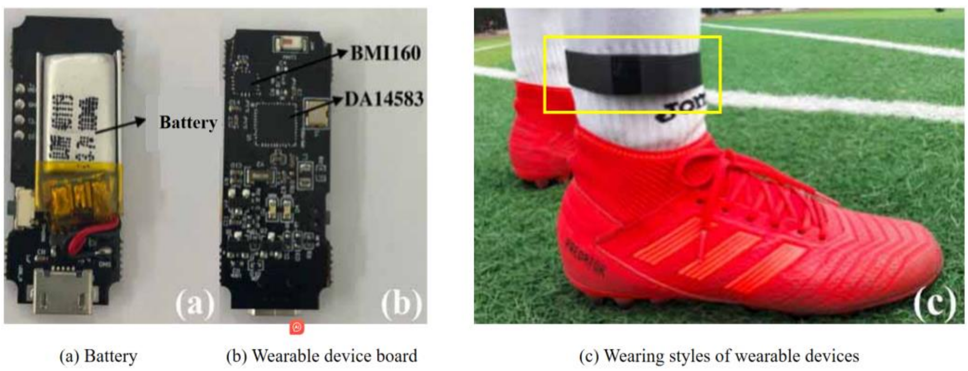


Figure 2: Architecture and Use of Wireless Wearable Devices

The wireless wearable device consists of key components, such as a MEMS motion sensor chip that has a three-axis gyroscope and accelerometer, a microprocessor unit with Bluetooth connectivity, a lithium battery, and a device switch. MEMS, or Microelectromechanical Systems, employ a three-axis gyroscope and accelerometer to gather motion data and convert the signals into unprocessed information (Ahmed & Al-Gayem, 2023). This gadget incorporates the BMI160 sensor produced by BOSCH. The DA14583 microprocessor, manufactured in Reading, UK, serves as a baseband radio processor equipped with a fully integrated radio transceiver that is specifically tailored for low-power Bluetooth. The BMI160 sensor is a compact and energy-efficient semiconductor that enables the measurement of 3D acceleration and angular velocity. This project involved the creation of a smartphone application that was designed to accept and present real-time data from the wearable device. The application comprises three functions: wireless networking, real-time data collecting and presentation, and cloud synchronization of the data. The gathered data is synchronized, presented, and kept locally. Moreover, the cloud-based technique allows for the distant storing of data. After finishing the process of collecting data, users can retrieve the analysis findings on the client side.

2.2 Data Acquisition

Eleven male soccer players were enlisted, comprising of five pros and six amateurs. The professional soccer players showcased their skills in over twelve national matches at the CFA Youth Academy, whilst the non-professional soccer players were novices at the university. A portable wireless wearable device was affixed to the participants' right ankle to ensure the comprehensive recording of vital data on soccer motions during the execution of fundamental soccer actions. Every individual executed a total of 20 passes using the inside of their foot and 20 shoots using the arch of their foot. The experimenters replicated these moves in the identical posture and were obligated to execute both the passing and firing maneuvers with a specific level of velocity and precision. Otherwise, the maneuver was deemed invalid and excluded from the count. Figure 3 depicts the experimental scenario used to collect data.

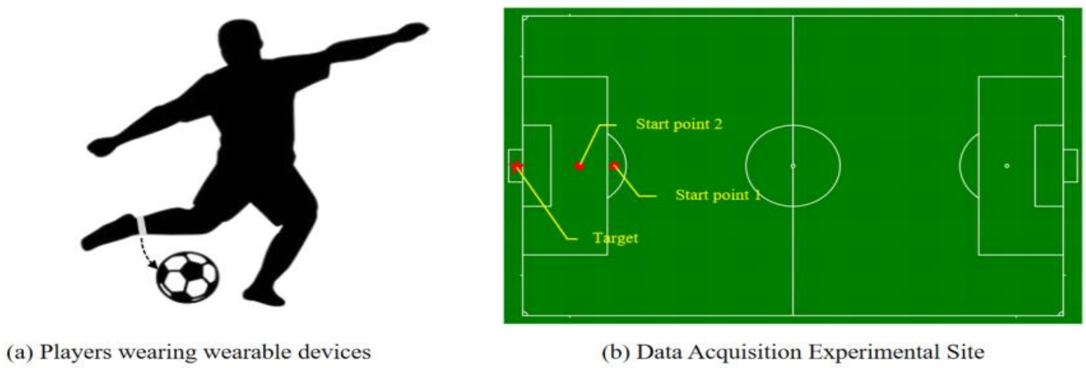
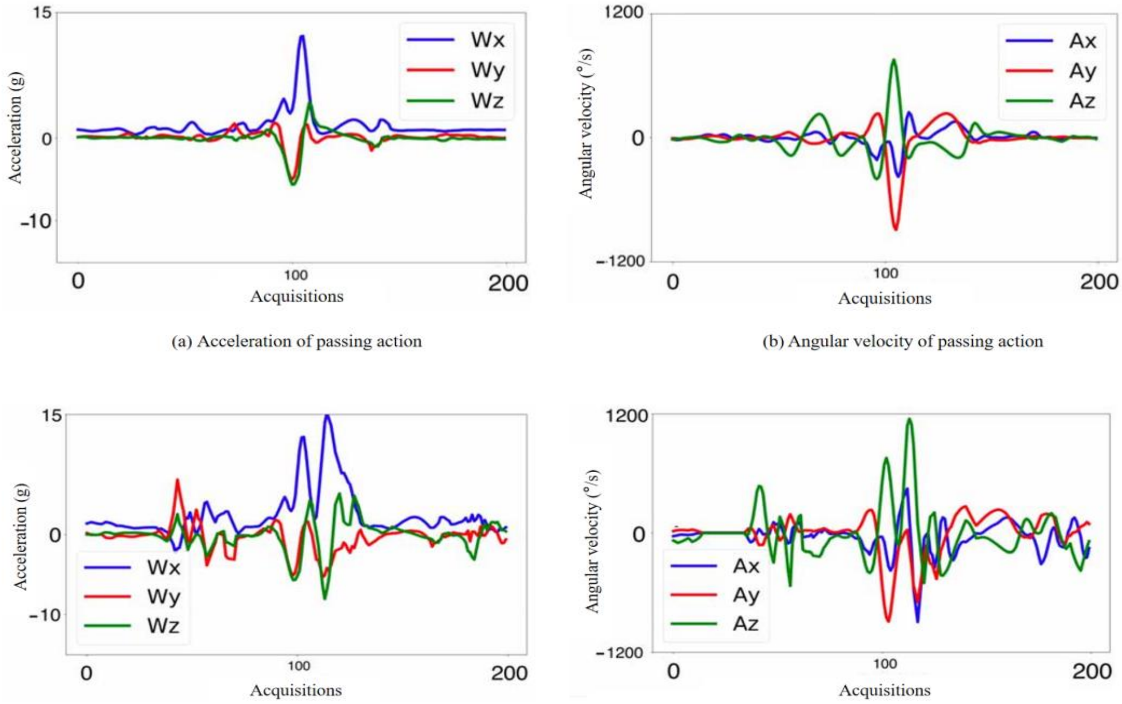


Figure 3: Data Acquisition Experiment Setup

Figure 4 shows the six-axis synchronization raw data of a professional athlete performing different soccer moves.



(a) Acceleration of passing action

(b) Angular velocity of passing action

(c) Acceleration of shooting action

(d) Angular velocity of shooting action

Figure 4: Professional Athletes Data Graphic Column

3. LSTM-based model for soccer action recognition and intensity analysis

3.1 LSTM

The Long Short-Term Memory (LSTM) model partially addresses the long-term dependency issue in recurrent neural network structures by incorporating gate control units and current connections within the neural units (Lindemann et al., 2021). In comparison to traditional recurrent neural networks, LSTM introduces input gates, forget gates, output gates, and internal memory units to each neuron, enabling selective retention and retrieval of historical information. LSTM constitutes a specialized network structure with three "gate" components, and its internal architecture is depicted in Figure5.

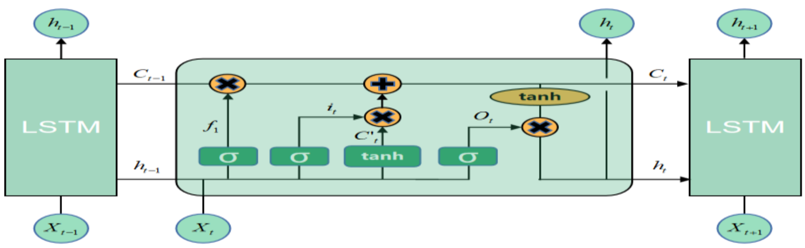


Figure 5: Diagram of the internal structure of the LSTM

The graphic represents the input gate, forgetting gate, and output gate as i, f, and o accordingly. The cell state is denoted by c and the output of the implied state is denoted by h. The activation functions used are σ and tanh. The input gate, denoted as i, operates within the value range of (0, 1). Its primary role is to assess the significance of the present input information prior to establishing a fresh memory. Subsequently, it regulates the magnitude of the newly produced component C'_t within the cell state C_t. The input gate structure is depicted by equations (1) and (2):

$$i_t = \sigma(w_t \cdot [h_{t-1}, x_t] + b_t) \tag{1}$$

$$C'_t = tanh(w_c \cdot [h_{t-1}, x_t] + b_c) \tag{2}$$

The purpose of the forgetting gate is to assess the relevance of the previous memory cell in the calculation of the current memory cell. It filters information and regulates the extent to which the input and output of the previous hidden layer are forgotten. Additionally, it controls the amount of information from the previous moment's cell state that can be transferred to the current moment's cell state. The objective is to regulate the retention or omission of the hidden cell state from the preceding layer, using a specific probability within the range of (0,1). The equation below depicts the construction of the forgetting gate:

$$f_t = \sigma(w_f \cdot [h_{t-1}, x_t] + b_f) \tag{3}$$

The current cell state in each LSTM cell is updated using the output values of the forget gate f and the input gate i. As shown in the figure, the new cell state C_t is composed of two components. The first component is determined by the previous cell state C_{t-1} and the forget gate f with a size of $(f_t \times C_{t-1})$. The second component is governed by the current cell state information C'_t and the input gate i with size $(i_t \times C'_t)$. The procedure for modifying the cellular state is illustrated by the subsequent equation:

$$C_t = f_t^i C_{t-1} + i_t C'_t \tag{4}$$

The output gate serves to separate the final memory from the hidden state and regulate the information that should be produced by the present neuron, based on the updated cellular state. This ultimately determines the most concealed state's final output. The equation below illustrates the construction of the output gate:

$$o_t = \sigma(w_o \cdot [h_{t-1}, x_t] + b_o) \tag{5}$$

$$h_t = o_t \times tanh(C_t) \tag{6}$$

The LSTM network structure is characterized by each gate (input gate, oblivion gate, output gate) having its own set of parameters. This is a crucial aspect of the LSTM network. Additionally, the formula for each neuron's structure, denoted as h, is composed of the current input x and the output of the previous hidden neuron. The value of σ is typically selected as the activation function, primarily serving as a gate, due to the fact that the output of the sigmoid function ranges between 0 and 1. This aligns with the conceptual interpretation of "off" and "on" in a physical sense. The tanh function serves as an activation function for the memory cell c mostly due to its output range of (-1,1). The primary rationale for selecting the hyperbolic tangent tanh function as the activation function for the memory unit is due to its faster convergence time compared to the sigmoid function, particularly when dealing with scenarios that involve a normal distribution centered around 0. When the input data lacks useful information, the forget gate f has a value near to 1, while the input gate i has a value close to 0. This ensures that valuable information from the past is retained. When the input sequence contains crucial information, the forget gate f will have a value that is nearly equivalent to 0, while the input gate will have a value that is nearly equivalent to 1. At this juncture, the LSTM model disregards previous memories and selectively retains crucial information in the present time. The three gate structures of the LSTM network, along with the memory unit, collectively regulate the output of the network. This enables the network to successfully manage the alteration of sequence information.

3.2 LSTM-based information processing model for motion recognition

Neural Network Layer Design A typical neural network contains an input layer, a hidden layer and an output layer. The input layer acts as a buffer memory throughout the network and is used to add data to the network. The number of layers and settings of the hidden layer are key to the design of a neural network, according to the Universal Approximation Theorem, when having a layer of linear output layer and a nonlinear excitation function, it can infinitely approximate the function that needs to be modeled, given enough neural network nodes and suitable parameters (Hings et al., 2020).

Although this theorem does not provide a theoretical reference for the specific number of nodes in a neural network, we can at least narrow the focus of our research to the number of neural network nodes. It is generally accepted that a moderate increase in the number of network nodes can improve prediction accuracy, but too many network nodes can also increase the overall complexity of the network, leading to spikes in computation and training time and overfitting problems (greater accuracy on the training set than on the test set). At present, there is no clear theory of the number of neural network nodes, or rely on experience in practice, but the number of nodes cannot be greater than the number of samples. In multi-classification problems, the output layer often uses a softmax excitation function as the fully connected layer, and its output can be viewed as a probability distribution that sums to one. In order to avoid overfitting problem, dropout is used to disconnect neurons with random chance to enhance the overall robustness of the model, and the probability of disconnection p is usually set to 0.5 (Li, 2019).

3.2.1 Loss Function Design

The loss function quantifies the discrepancy between the projected value of model for $\hat{y}$ and the true value y. It is always greater than or equal to zero. The loss function is iteratively optimized using optimization techniques such as gradient descent, Newton's method, and others. If the value decreases, it indicates an increase in the model's fitting capability. There exist numerous varieties of loss functions, with the often-employed ones being:

(1) The mean-square error (MSE) function is calculated by the formula.:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2 \tag{7}$$

(2) The cross-entropy loss function, which measures the difference between two probability distributions. p is the true probability distribution and q is the predicted probability distribution, and is calculated as follows.

$$H(p,q) = \sum_i p(i) * log\frac{1}{q(i)} \tag{8}$$

When the sigmoid function is utilized as the activation function, the majority of values along the curve of the function have low gradients. Using the mean square error function as the loss function decreases the rate at which the weights are updated. Given that this research deals with an issue involving many classes and employs a recurrent neural network of the LSTM type, the soft max function will be used at the output of the network to transform it into probabilities. Using the cross-entropy loss function in this situation eliminates the necessity of the sigmoid derivative. Therefore, while selecting Categorical Cross-Entropy as the loss function is a more suitable choice. The function is described in a comprehensive manner below:

$$Loss_i = -\sum_j t_{i,j}\, log\left(p_{i,j}\right) \tag{9}$$

The formula uses the variables p to represent the predicted value, t to represent the actual classification, i to indicate the location of the data, and j to represent the location of the classification in the prediction.

4. Experiments

4.1 Experimental Design

A series of data gathering experiments were conducted to obtain 126 sets of passes and 108 sets of shots on goal. The dataset was partitioned into training and test sets through random sampling, with 80% assigned to training and the remaining portion designated as test data. To validate the training model, a batch size of 200 was utilized, and the model underwent 3500 iterations. Additionally, the input data was standardized. The Keras library provides various optimization algorithms, including Stochastic Gradient Descent (SGD), RMSProp, and Adam optimizer. For this study, the Adam optimizer was chosen for model optimization in the tests. The F1 scores and mean accuracies (mAP) were employed to evaluate the performance of the movement classification subtask model. For each activity type, the quality of the movement intensity estimation sub-model was assessed using the mean absolute percentage error (MAPE). The occurrence of mild overfitting in the models can be attributed to the inherent characteristics of the approach employed and the scarcity of available data. Upon conducting the parametric grid search, the best model's final hyper parameters are determined as follows: a learning rate of 0.0015, weight decay of 0.0001, neural unit discard rate of 0.5, batch size of 256, 3000 iterations, and a regularization constant of 0.00015. The most effective model configuration consists of a single-layer model with 32 hidden units per LSTM layer. This choice is based on the observation that a lesser number of hidden units fails to adequately learn the feature information, while a greater number of hidden units only marginally improves the F1 score while considerably increasing computational costs.

4.2 Experimental Results and Analysis

The outcomes for the action recognition subtask in the multitask deep learning model are displayed in the columns on the far right of Table 1. The recognition job encounters difficulties due to the restricted sophistication of the two-layer LSTM with 16 neural units, leading to insufficient information acquisition. On the other hand, using a two-layer LSTM with 64 neural units results in unnecessary intricacy. The optimal model consists of a single-layer Long Short-Term Memory (LSTM) with 64 neural units, which achieves the maximum accuracy on both the training and test datasets.

Table 1: Comparison of single-layer L1 and multi-layer L2 action recognition results

MODEL	F1-SCORE			MAP	
	Player1	Player2	All Data	Training Set	Test Set
L1-16	0.7098	0.8709	0.7678	0.9174	0.9374
L1-32	0.9446	0.9149	0.8075	0.9548	0.9440
L1-64	0.7865	0.9304	0.8220	0.9980	0.9855
L2-16	0.7364	0.7905	0.6925	0.8396	0.8826
L2-32	0.7504	0.8502	0.7923	0.9068	0.9206
L2-64	0.7827	0.9764	0.8095	0.9119	0.9000

The experiments aimed to compare models with varying numbers of hidden units and layers, and to evaluate the impact of incorporating an extra fully linked layer prior to the output layer on the model's output. The outcomes are displayed in Table 2. It has been observed that incorporating an extra completely linked layer leads to a decrease in the Mean Absolute Error (MAE) when considering the average of the cross-validation outcomes. Furthermore, it is evident that increasing the number of concealed units enhances the model's ability to accurately correlate the input wearable data with count estimations, hence boosting the precision of motion intensity estimation.

Table 2: Comparison of single-layer L1 and multi-layer L2 motion intensity results

MODEL	FULLY CONNECTED LAYER OR NOT	MAE		
		Player1	Player2	All data
L1-32	×	2.5941	1.5304	1.6843
L1-32	√	1.0629	1.6167	0.9553
L1-64	×	1.0570	1.0670	0.8367
L1-64	√	0.7252	0.5882	0.5752
L2-32	×	1.0824	0.5041	0.6088
L2-32	√	1.6107	0.6760	0.6218
L2-64	×	0.7189	0.6686	0.5949
L2-64	√	0.5874	0.6152	0.5325

The optimal approach for predicting motion intensity in the single-task model involves employing a two-layer LSTM network including 64 neural units, in addition to incorporating a fully connected layer with an additional 32 neural units. The experiment's results are located in the final row of the table. The incorporation of a dual-layer LSTM layer improves the extraction of significant features in the model for estimating motion intensity. Nevertheless, an LSTM network with only one layer, consisting of 64 neural units, and a fully linked layer, manages to achieve similar performance while having a lower level of complexity. Furthermore, the single-layer model exhibits the highest mean F1 scores in the motion action categorization model. The average F1 score for the sub model specifically designed for the action recognition task was 82.20%. The effectiveness of the comprehensive multitasking approach is compared to the results of the single-tasking strategy. In order to assess the efficacy of the multitasking model, we conducted a comparison of its F1 scores and mAP measures with those of the single-tasking model. The results are displayed in Table 3.

Table 3: Comparison of experimental results between single-task models and multi-task models

MODEL	ACCURACY	F1-SCORE	MAP	MAE	MAPE-%
SINGLE-TASK LSTM-32	0.8362	0.8205	0.7629	0.9250	37.1060
SINGLE-TASK LSTM-32	0.8700	0.8473	0.8036	0.5779	18.7988
MULTI-TASK LSTM-32	0.8123	0.7928	0.7400	0.5935	16.6777
MULTI-TASK LSTM-32	0.8605	0.8323	0.7910	0.6106	22.8650

The top scores on all metrics were attained by the single-task, single-layer LSTM network with 64 neural units and no fully connected layer for the action recognition task. On the other hand, when it comes to estimating the intensity of motion, the LSTM model with a single job and a single layer, consisting of 64 neural units and a fully connected layer, produced the most accurate results with the lowest error values according to the Mean Absolute Error (MAE) metric. Nevertheless, employing a model size of 32 neural units resulted in the lowest error in the MAPE measure. This can be attributed to the model's diminished complexity and its ability to prevent overfitting, as opposed to the model with 64 neural network units. This reduction process eliminates data points that deviate significantly from the average, which in turn reduces the Mean Absolute Percentage Error (MAPE) and improves the accuracy of action classification. These findings indicate that using a multi-task model is more advantageous than using several single-task models for enhancing the performance of motion intensity estimate, but with a little decrease in action classification accuracy. To lessen the consequences of this compromise, one might employ methods like using moving average filters to reduce noise and smooth out data streams. While our model demonstrates strong performance on actual datasets, its effectiveness is somewhat restricted by limitations in data quantity. To mitigate the risk of overfitting, we employ feature augmentation and parameter tuning techniques during training. Additionally, we prioritize the ongoing acquisition of data to improve the accuracy of recognition. The models were assessed by comparing their performance in various datasets, including UCI-HAR, BaSA, and Stanford-ECM. This evaluation aimed to determine whether a multi-task model utilizing sensor data enhances the motion classification task. The results obtained for the model are summarized in Table 4.

Table 4: Experimental results of multi-task modeling based on UCI-HAR public dataset

MODEL	DATA TYPE	CLSF. (MAP)	REG.(MAE)
STM-UCI	a	0.8976	\
STM-UCI	a,g	0.8989	\
LSTM BM-UCI	a,g	0.8881	\
LSTM MTM-UCI	a,g	0.9299	\
STM-BASA	a,g	0.7326	0.2247
LSTM BM-BASA	a,g	0.8101	0.7867
LSTM MTM-BASA	a,g	0.8266	0.7053
STM-ECM	a	0.3425	0.2334
LSTM BM-ECM	a	0.5233	0.7655
LSTM MTM-ECM	a	0.7884	0.7039

a：acceleration; g：gyro; BM: Base Model; STM: Single-Task Model; MTM: Multi-Task Model

The UCI-HAR dataset initially included the measurement of total acceleration as a data feature. The classification accuracies achieved by the single-task model employing this dataset demonstrated satisfactory performance, however inferior to the outcomes reported in the current research on the suggested model. Consequently, the inclusion of gyroscope data was implemented to augment the information included in the feature data and retrain the model. However, the model did not yield superior results when using gyroscope data compared to using solely acceleration data. The multitasking model's performance was diminished in comparison to the single-task model due to the amalgamation of two autonomous jobs into one, and the utilization of direct estimation of acceleration counts and gyroscope data as input. Nevertheless, the performance of the action categorization subtask model in the multitask model shown a substantial improvement, surpassing the recognition rate achieved by the single-task model. Nevertheless, within our dataset, the inclusion of gyroscope data as input in conjunction with acceleration data enhances the precision of action classification for all models. The multitasking model was subsequently trained using the BaSA dataset to assess its performance in handling multi-sensor data challenges. The data was reduced in frequency to 50Hz in order to train the model. The findings indicate that the model has high precision in action categorization, but its accuracy in motion intensity estimation is comparatively lower. This discrepancy arises due to the multitasking model's inclination to prioritize enhancing classification accuracy, which comes at the cost of motion intensity estimation. Ultimately, the multitask model underwent evaluation on a specific portion of the Stanford-ECM dataset. The original dataset named Talking was used to merge the data characteristics and identify six groups. Transforming the activities of sitting and completing tasks to the activity of sitting and engaging in conversation. Combine the actions of standing and standing in line into the action of standing, which includes sitting, standing, walking, running, descending stairs, and ascending stairs. The sub-model achieved an outstanding result of 0.2247 MAE for the motion intensity estimate test. However, its performance for the action categorization challenge was not excellent in terms of mAP. The presence of an imbalanced distribution of classes in the Stanford-ECM6 dataset results in a significant bias in the model, but the variance remains low.

5. Conclusion

This study takes IoT technology as the background to construct a soccer movement recognition and evaluation method based on wireless wearable devices. Using the data collected by sensors in soccer games and training to recognize and evaluate athletes' movements, it can reflect the athletes' movement status in real time, and when the athletes experience movement deformation caused by fatigue or injury, it can prompt the athletes and coaches to make adjustments to the training content in a timely manner. The main conclusions of this paper are as follows:

(1) The IoT-based wearable sensing technology is constructed to consist

of a wireless wearable device, a mobile device and a cloud-based data processing platform. The wearable device adopts the BMI160 sensor from BOSCH and the DA14583 microprocessor unit produced by the Reading Company in the U.K. The device realizes the real-time monitoring of the motion characteristic data of the ankle part of the soccer movement, and the device is compact and lightweight. (2) Based on the LSTM model, the soccer action recognition and intensity analysis model is constructed to process the sports data of soccer players. Through experimental verification, the model has excellent action recognition ability.

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