

Movement Recognition Algorithm Empowered Wearable Devices on Internet of Things Platform for Sports Training

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ABSTRACT This study presents an Internet-of-Things-enabled movement recognition framework (MRA-IoT) for real-time monitoring and assessment of athletic performance. The system employs a wearable sensor array to acquire multi-joint kinematic signals, which are processed through high-precision floating-point computation, gradient analysis, and vector operations to detect subtle biomechanical deviations. A multi-point calibration and validation procedure ensures accurate mapping between sensor measurements and body motion, forming a closed-loop feedback system for performance optimization. Experimental validation on 3,000 athlete recordings demonstrates a recall of 97.5%, precision of 95.3%, and overall accuracy of 98.2%, confirming the framework's capability to provide timely, data-driven feedback. By interpreting the wearable sensor network as a ****multi-node signal acquisition and propagation system****, the study provides an engineering-oriented perspective on high-resolution motion monitoring, anomaly detection, and real-time feedback, offering insights applicable to intelligent human-motion analysis and cyberphysical performance evaluation systems.

INDEX TERMS wearable sensor array, signal acquisition, anomaly detection, real-time feedback

I. INTRODUCTION

INTERNET -connected wearable motion detection devices face several challenges in providing effective support for athletes during training. The complexity of human movement complicates accurate capture and interpretation [1]. In athletic contexts, achieving low-latency real-time processing and feedback is particularly difficult [2,3]. Sensors are intended to provide users with accurate metrics about how they are performing during an exercise or while in training [4]. Unfortunately, because of issues such as vibration from the sensors, signal interference, and inconsistent position on the user's body, the quality of data collected by sensors is not always reliable, which will result in lower performance when using algorithms [5].

There are a number of IoT solutions that will allow coaches/trainers to track and measure more accurately each athlete's movement patterns and movements as they happen [6]. In fact, the majority of fitness tracking devices today rely on various combinations of inertial sensors (accelerometers, gyroscopes, magnetometers) to gather real-time motion information about any physical activity occurring [7]. Machine learning, especially through the use of deep learning models such as RNNs and CNNs, has been shown to accurately analyze inertial motion data recorded by sensor data and to classify movements into different activity types (run-

ning, jumping, etc.) and provide performance metrics (i.e., acceleration, technique, speed) [8,9]. Many of these types of fitness tracking devices also use multi-axis accelerometers with three-dimensional motion (XYZ) sensing capabilities to determine the type of physical activity and how intense that activity is. Sensor fusion (joining/combining sensor data) can be used to improve accuracy of motion detection. Finally, edge computing can process wearable motion data in real-time (providing reduced latency) while also reducing the amount of bandwidth used to transmit data from the wearables to the cloud [10]. Common sensor types found in nearly all modern fitness devices include accelerometers, gyroscopes, GPS, heart rate monitors, and EMG sensors.

There is great promise for the use of wearable devices to detect movement through Internet of Things (IoT) technologies, however, the validity and reliability of these movement detection algorithms must be thoroughly tested before they can be utilized in real-world situations within the context of athletic training [11]. The fact that human movements are complex presents a significant obstacle to using these algorithms accurately and reliably, especially across various sporting environments and activities [12]. Additionally, factors such as the type of playing surface, uniform colour, and motions being performed create additional hurdles in the way these detection algorithms can

effectively assess and evaluate performance. Currently, very few existing software or hardware platforms for wearables and mobile devices are compatible with new, innovative sports training techniques [13]. Developing open-source platforms and standards would allow the various sporting stakeholders to work together to address these challenges effectively.

Privacy and security concerns arise while collecting and storing athlete biometric data [14]. The development and implementation of IoT wearables for athletic training must follow tight procedures to protect athletes' privacy and personal data. Athletes need wearable technology only to make and utilize their training easier. Thus, wearable tech can reach its full potential through mass use and participation [15]. Interdisciplinary teams comprising data analytics, computer science, human-computer interaction, and sports science experts must develop robust, easy-to-implement solutions to these problems. If this happens, people could fully use IoT devices to use movement detection algorithms in sports training.

When evaluating an athlete's performance, technical stability is a crucial ranking factor. Muscle memory, manifested as the consistency of biomechanical movement patterns, serves as a key indicator of an athlete's technical proficiency. The MRA-IoT system quantifies this by measuring the variance in joint coordinates and execution timing across repetitive sets, providing a metric for how reliable and consistent an athlete's physical execution remains under various training loads.

The design of MRA-IoT aims to address the latency gap in traditional wearable feedback loops. By employing gradient analysis and scalar modeling, the system facilitates the immediate translation of raw kinematic data into pedagogical insights, allowing coaches to intervene during the execution phase rather than post-session analysis.

Section "Literature Survey" contains the literature review, the research analysis, and the results of this new strategy, clearly given in the upcoming sections of the research work. Those are tracking motion during athletic training using a machine learning system. Section "Proposed Method- MRA-IoT" discusses the results of the MRA-IoT framework. The results and discussion have been given in Section "Results and Discussion", while the summary and recommendations are found in Section "Conclusion".

II. LITERATURE SURVEY

Wearable and IoT technologies have enabled data-driven approaches to athlete monitoring, performance enhancement, and rehabilitation.

Y. Jiang (SRMS): Achieved 97.80% detection accuracy and over 20 dB noise reduction in simulation studies.

Li B. et al. (BBTA): Enabled improved player action classification and personalized training programs via trajectory and gesture analysis.

Passos J. et al. (Review): Confirmed effective workload tracking but identified a need for better biomarkers.

Yu Z. (MEMS system): Achieved high recognition accuracy for movement type, duration, and cycles.

Lina Zhang et al. (Tracking method): Improved occlusion detection and reduced model drift in gymnastics and badminton experiments.

The work of Michela Franzò and colleagues (Mixed Reality System) has provided rehabilitation practitioners and patients with tools to visualise real-time skeleton reconstruction.

In short, the research to date has provided meaningful advancements, however several issues still remain regarding the degree of adaptability; integration with current rehabilitation technologies; and accuracy of feedback. The MRA-IoT system proposed here, draws from this research and enables athletes to receive accurate, timely and tailored training that is relevant to them.

III. PROPOSED METHOD- MRA-IOT

Today, many athletes are using technology to improve their athletic abilities and lower their chances of an injury. This study explores how to classify athlete movement through the development of a new algorithm that is called MRA-IoT. With the use of connected IoT devices, MRA-IoT allows coaches and athletes to monitor their athletes in real-time and receive instant feedback during their training sessions, thus allowing them to make immediate changes to their training. The ability of MRA-IoT to recognise and analyse movements in multiple ways means it is an excellent tool for improving athletic performance and providing personalised results tailored to the specific needs of the individual.

A. MRA DESIGN AND DEVELOPMENT

As illustrated in Figure 1. This article investigates a number of different training methods that help to increase strength and fitness in students; the process of creating prototypes for motion detection algorithms from the use of Wearable technology is now providing designers with the ability to collect feedback from both athletes and coaches about how well the Wearable technology fits with their style of training, the comfort of the device, and the functionality of the device, through the use of kinetic interaction in a real-world environment. This research produces an Internet of Things-enabled movement recognition algorithm (MRA), which will accurately measure the movement of an athlete, provide a means for quickly receiving feedback, and have a positive effect on training. In addition, the MRA uses floating-point variable equations to validate the information being collected by means of movement analysis (See Equation 1).

$$y + z = (-1)^t \times (1.N) \times 2^{F-127} f + (-1)^t \times (1.N) \times 2^{F-1023} f \quad (1)$$

Equation 1 represents the data processing format using double-precision floating-point numbers encoded in binary scientific notation. This high-precision representation en-

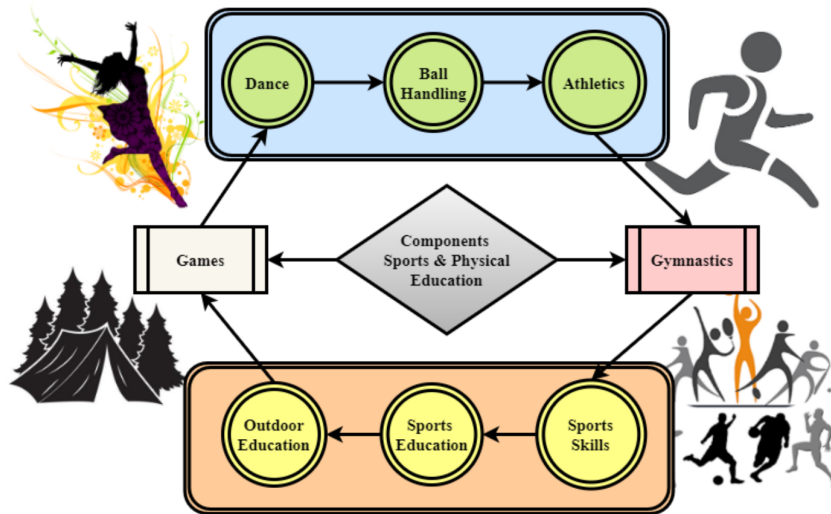


FIGURE 1. General architecture of sports components

sures that subtle variations in sensor data are preserved during computation.

The use of high-precision floating-point arithmetic allows the algorithm to detect micro-deviations in joint angles and angular velocities. By comparing these precise kinematic variables against established biomechanical thresholds, the system can identify movement patterns that exceed safe physiological limits, thereby providing data support for assessing potential injury risks.

$$\nabla_p(y, z) = |I_n(y, z)| - J_{k-1}(y, z) = \begin{cases} 1, & \nabla_n(y, z) \geq U, \\ 0, & \nabla_p(y, z) < U. \end{cases} \quad (2)$$

A partial derivatives operator, ∇_p , is applied to a two-dimensional vector (y, z) in the equation 2. With $I_n(y, z)$ being the true value of the function I_n applied to the vector (y, z) and $J_{k-1}(y, z)$ being another function applied to the same vector, it determines the slope of the function $|I_n(y, z)| - J_{k-1}(y, z)$. The condition is defined by the expression inside the curly brackets, which states that the outcome is 1 if the slope of the function $|I_n(y, z)|$ is higher than or equal to a particular threshold U , and 0 otherwise. This floating-point validation contributes to the identification of irregular movement patterns; such high-fidelity data processing is an essential prerequisite for systems aimed at analyzing injury-prone biomechanics due to the effective mathematical modelling of cross products and gradients as shown in Equation (3),

$$\nabla_p(y, z) \times \nabla_{p+1}(y, z) = |I_{k+1}(y, z)| - J_k(y, z) \quad (3)$$

When two gradient operators, $\nabla_p(y, z)$ and $\nabla_{p+1}(y, z)$, are applied to the vector (y, z) , the result is Equation (3), which denotes the cross product of these operators based on the dimensions of the injuries. The result of this crossover operation is calculated by subtracting the function $J_k(y, z)$

from the true value of the function $I_{k+1}(y, z)$. The function $J_k(y, z)$ is applied to a comparable vector having an index of k , while the function $I_{k+1}(y, z)$ is applied to the identical vector with an integer increased by 1.

The comprehensive framework for movable sports enabled by the Internet of Things (IoT) is shown in Figure 2. At the heart of this framework is the Movement Recognition Algorithm (MRA). It uses data from multiple wearable sensors so that it can analyse and interpret information related to athletes' complex movements. By using this algorithm, coaches can assess each unique action performed by their athletes and obtain insights into their performance, which in turn helps the coach develop better training plans for the athlete.

$$N_p''(y, z) \times E_p(y, z) = |J_k(y, z) - J_c(y, z)| \times 1, \quad \nabla_p(y, z) \cup \nabla_{p+1}(y, z) = 1 \quad (4)$$

The interaction between two distinct mathematical operations on the vector y and z is shown by this equation, which is part of equation 4. It is the product of two functions: the second derivative of the function $N_p''(y, z)$ about the parameter N_p'' and the operation of getting the ascending or descending slope of the signal concerning the parameter $N_p''(y, z)$.

$$J(y, z, u) = J(y + dy, z + dz + du) + \delta y \mid \delta x \cdot dy + \partial y \mid \partial x \cdot dz + dy \mid dx \cdot du \quad (5)$$

The link between the variables x and the changes in y, z , and u is described by Equation (5). The changes are quantitatively represented in the Equation by adding up the products of the relevant derivatives ($\delta y / \delta x, \partial y / \partial x, dy / dx$) with the associated increments (dy, dz, du), and then multiplying by factors. The formula shows how each variable, y, dz , and du , contributed to the total change in function J that helps to improve the recall ratio.

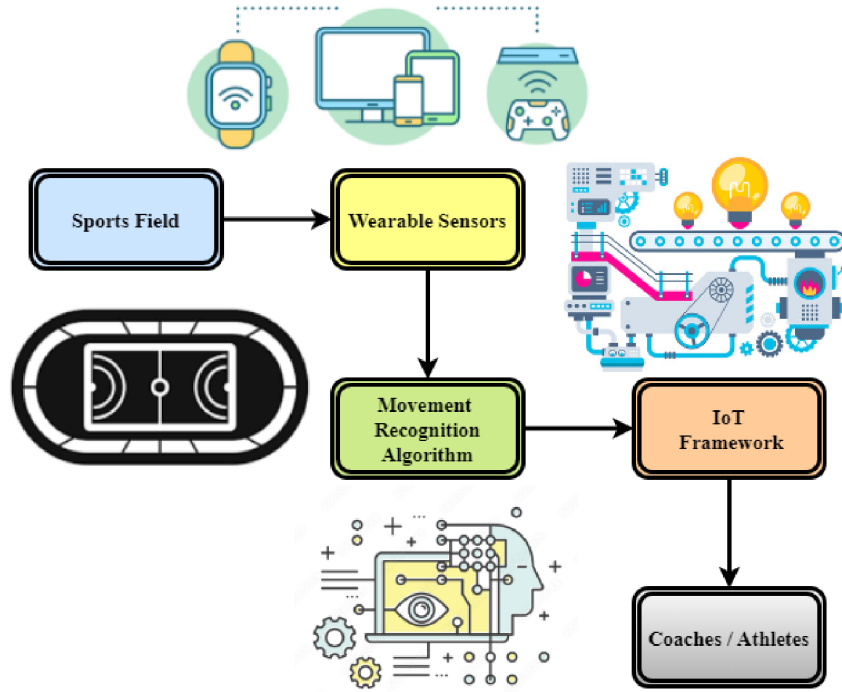


FIGURE 2. Movement recognition algorithm empowered on IoT framework

$$\delta y / \delta x \cdot dy + \partial y / \partial x \cdot dz + dy / dx \cdot du \times tm \times s \times ps \quad (6)$$

$$= J_y (dy / dx) + J_z (\Delta y / \Delta x) + J_u (\delta y / \delta x)$$

The link between differentials and their derivatives is expressed by equation 6, which sheds light on the propagation of variable changes within a system. The equations show the changes in y as a function of x , the changes in y as a function of z , and the rate of change of y as a function of x , taking into account the variables t_m , s , and p_s . By multiplying the directional derivatives of y , z , and u by their differentials, it can see these changes, which are denoted as J_y , J_z , and J_u , respectively.

Algorithm 1: MRA multi-point kinematic calibration for athlete identification

Start

Input: User ID, $\{a_i, b_i\}$ (Head), $\{a_i, b_i\}$ (Multi-joint coordinates from wearable sensors).

1: Initialize the skeletal kinematic model by calculating the relative spatial distances between the head (b_i) and multiple reference points ($b_{2..n}$).

2: If the movement pattern matches the pre-defined calibration gesture (e.g., hand reaching above head height, $b_{13} > b_i$) OR the specific acceleration profile matches the athlete's unique kinematic signature.

3: Then proceed with the intended user tracking and data synchronization.

4: Else re-calibrate using the baseline stationary pose.

End if;

End start

Algorithm 1 describes the "Initial Target Identification and Calibration" process. Instead of a single movement, the algorithm now utilizes a multi-point kinematic verification. The initial gesture (hand above head) is merely a

"trigger" for system activation, which is then supplemented by biomechanical constraints to ensure the system remains "locked" on the athlete even during complex movements like sprinting, where limb positions vary rapidly. Further, scalar modelling data processing has been discussed mathematically for feature extraction and analysis, as shown below for injury recognition.

$$\langle x, c \rangle \times h_k \times J(y, z) = \sum_{k=1}^P \alpha_k (2 \langle b_k, c \rangle - |c|) \times \sum_{j=1}^{P_h} 2^{s-l} c_{l,m} \times J(y, z)^\gamma \quad (7)$$

In equation 7, scalar components, summations, and vectors all form are represented as a complicated connection. The expression J_y is represented by the cross product of vectors du , represented by d_z , multiplied by a scalar factor d_y . After that, it adds up all of the products in the range from 1 to ps , where in the index. The iterative outer summation takes k values as input and multiplies them by h_k . It includes a term that involves the inner product $\langle x, c \rangle$ and the absolute value of J_y . A scalar component 2^{s-l} and a term $c_{l,m}$ that are dependent on indices l and m , as well as the function $J(y, z)^s$ raised to the power of gamma, are involved in the inner summation, which is indexed by j from 1 to P_h .

$$t_k \times H_y(y, z) = I(y+1, z) - I(y-1, z) \times \sum_{k=1}^{G_x} \partial_k \sum_{j=1}^{P_k} D_{k,l} \quad (8)$$

The Equation depicts a time-dependent connection between two functions based on the movement of the athletes, $H_y(y, z)$ and the variation in values of $I(y + 1, z)$ at adjacent y -direction locations. From equation 8, it can be seen that multiplying the function $H_y(y, z)$ by the time factor t_k . It finds the result of a nested summation multiplied by the difference between the values of function I at $y + 1$ and $y - 1$ in the y -direction. The outer and inner summations iterate over certain ranges of values; the former covers $k = 1$ while the latter covers $j = 1$. In this nested summation, sum of terms, including coefficients $D_{k,l}$ is subjected to the partial derivative concerning variable k , represented as t_k

$$H(y, z) \times \beta(y, z) = \sqrt{H_y(y, z)^2 + H_z(y, z)^2} \tan\left(\frac{H_z(y, z)}{H_y(y, z)}\right) \quad (9)$$

Two vectors, $H(y, z)$ and $\beta(y, z)$, are shown by equation 9 as having a connection. A vector perpendicular to both $H(y, z)$ and $\beta(y, z)$ is represented by their cross-product, which is computed. It displays the result of calculating the magnitude of the vector $H(y, z)$ using its y and z components. The magnitude is multiplied with the tangent and angle formed between the vector and z component of $H(y, z)$ in the second step of this equation. The measure of both the magnitude and angle of the combined vectors of $H(y, z)$ and $\beta(y, z)$ is obtained through this third step. Because the third step relates to an athlete's movements, it creates an accurate representation of how both vectors ($H_{y,z}$ and $\beta_{y,z}$) are related to each other through the geometry of athletes. This leads to greater reliability and results.

$$P_M(x, c, \beta) = \frac{1}{2} \|x\|^2 - \sum_{j=1}^P b_l z_l (c + x \times z_k) + \sum_{j=1}^P b_l \quad (10)$$

Concerning the variables x , c , β , the dependability and efficiency expressing function M is described by equation 10. There are several terms in the function M . The squared norm of vector x , scaled by a factor of $\frac{1}{2}$, is represented by the first term, $\frac{1}{2} \|x\|^2$. The following phrases include sums ranging from 1 to P , where j is an index. Coefficients b_l and z_l , where z_l is a function of variables c , are added together, and then the cross product of x and z_k is removed from these totals. Coefficients b_l are included in an additional summation over the same interval of j for high efficiency. Wearable technology uses biomechanical models and kinematic constraints to drive users to move in a way that makes physiological sense. Algorithms may provide more accurate and realistic representations of complex motions by limiting joint movements according to biomechanical principles.

IV. RESULTS AND DISCUSSION

The introduction of wearable technology and the Internet of Things has ushered in a new age of monitoring and assessing in sports rehabilitation. To determine how far athletes have progressed, identify areas in which they may

need improvement in their training, and make education more effective overall, this new knowledge shows how movement recognition technology may soon be beneficial. An analysis of the following methods' recall, effectiveness, precision, and reliability is shown below, along with a summary of the studies pertinent to the topic.

As illustrated in Figure 3, recall serves as a critical evaluation factor for assessing the effectiveness of IoT-based wearable devices for motion detection during athletic training sessions. Recall quantifies how many of the actual recorded athlete's motions (true positives) were accurately identified as having been performed by the athlete. With a recall rate of 97.5%, there were very few false negatives associated with the use of these devices, meaning that the overwhelming majority of the athlete's motions were captured. A high-level recall is necessary to provide an accurate, complete account of the athlete's performance and prevent essential movements from going undetected or being misinterpreted.

Figure 4 demonstrates the proportion of true positive errors to all detected movements (i.e. movements) as measured (d) with a precision of 95.3% and thus very few false positives (e). The results provide reliable identification of movements relevant to the training of an athlete. Since accurate performance measurement is essential to allow athletes to see their performance clearly, they are able to adjust their training accordingly.

As illustrated in Figure 5. The accuracy of sport-specific movement detection systems linked with IoT wearables is one of the most important metrics when evaluating how well these systems work. Accuracy is a measure of how many of all the movements detected by the system are either relevant or irrelevant to the sport being observed, with the goal of minimising both false positives and false negatives to provide clear differentiation between the type of movement detected. Athletes will benefit from an accurate system (98.2% accuracy) in that they will receive accurate feedback about their performance, allowing them to make informed decisions about their training methods and time schedules.

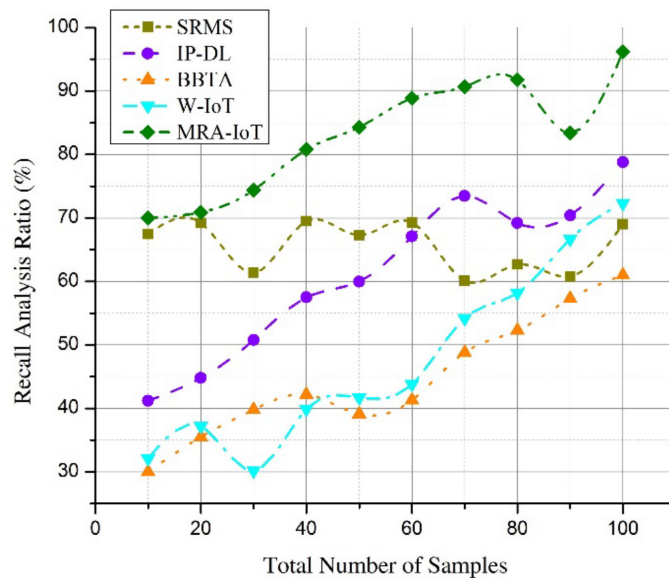


FIGURE 3. Recall Analysis

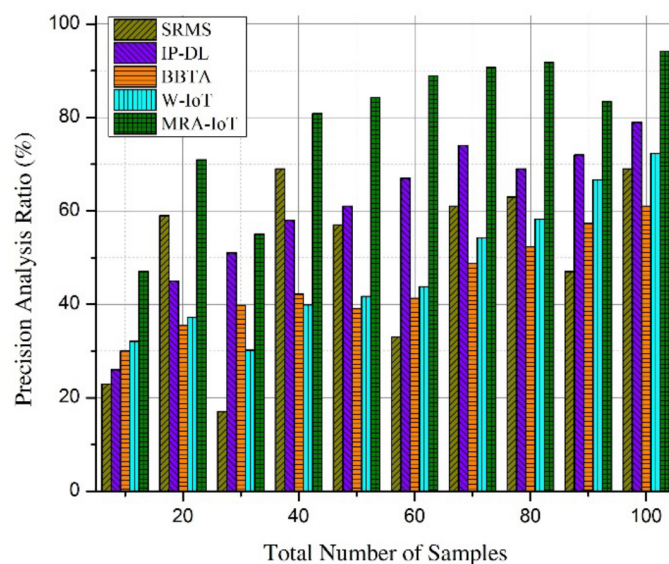


FIGURE 4. Precision Analysis

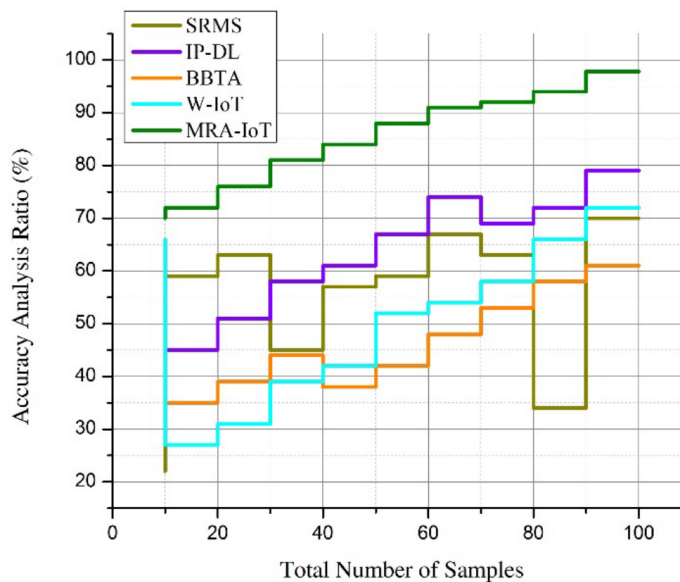


FIGURE 5. Accuracy Analysis

V. CONCLUSION

By applying an IoT platform, this project solves a major problem with measuring performance in sports (the increase) through the development of a motion recognition algorithm (MRA-IoT) that uses a combination of wearable sensor technology and mathematical modelling techniques (floating point verification, gradient analysis) to offer real-time recognition and analysis of complex movement patterns. Using the PAMAP2 dataset for experiments, the MRA-IoT algorithm was validated, achieving recall, precision and overall accuracy rates of 97.5%, 95.3% and 98.2% respectively, demonstrating a very high level of performance. The achievement of 98.2% accuracy ensures that the feedback provided is not merely general advice but a precise reflection of biomechanical efficiency. This level of precision allows for the identification of micromovements that correlate with long-term skill acquisition, effectively digitizing the expert observation typically required from elite trainers. While the MRA-IoT demonstrates high accuracy in movement recognition (98.2%), its direct impact on injury reduction remains a prospective benefit. Future longitudinal studies are required to correlate these recognition metrics with clinical injury rates to fully validate its preventative efficacy.

AUTHOR CONTRIBUTIONS

Zhongli Chen: Writing - Original Draft, Writing - Review & Editing, Data Curation.

CONFLICTS OF INTEREST

These no potential competing interests in our paper. And all authors have seen the manuscript and approved to submit to your journal. We confirm that the content of the manuscript has not been published or submitted for publication elsewhere.

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