Artificial Intelligence of Things in Sports Science: Weight Training as an Example

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The interdisciplinary nature of sports science introduces challenges such as multifaceted data collection, accuracy in knowledge formation, and equipment usability. Artificial intelligence of things (AIoT) technology presents a feasible solution adaptable to different sports. Taking weight training as an example, we apply AIoT technology to these challenges.

Sports science is a discipline that studies how the human body works during exercise and how sports and physical activity promote health and performance from cellular to whole-body perspectives. The field is an interdisciplinary science that involves areas of physiology, psychology, anatomy, biomechanics, biochemistry, and biokinetics.

The most common causes of sports injuries are usually related to improper mechanics and fatigue. Conventional training typically involves open kinetic chain, closed kinetic chain, or core strengthening exercises.

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Since 1992, Japanese athletes have used beginning movement load training (BMLT) in athletic training.[11,12] Athletes in track and field, baseball, swimming, and football have made significant progress over the past few years. However, most sport performance enhancement methodologies used today, such as weight training and BMLT facilities, seldom leverage artificial intelligence of things (AIoT) technology to enhance accuracy and precision. Coaches and doctors currently rely on their past experiences in structuring training methods and conducting analyses, which are usually not precise and may result in inappropriate and ineffective training or treatment. Manual and inconsistent recording of the athletes' body conditions in the training process is regularly seen. Moreover, the existing training processes lack the predictive analysis capability of mathematical modeling.

AIoT technologies integrate the technologies of AI, deep learning, big data, cloud computing, and the Internet of Things (IoT) and have been successfully applied to many areas. The challenges to achieving the goals of precision sports include data collection, IoT accuracy and usability (user experience), and AI model analysis and validation. In this article, we investigate the advancement of sports science by applying AIoT technologies, particularly in the area of weight training.

We describe the sport informatics and analysis system (SIAS) first, followed by a sport AIoT system. The SIAS resides in the cloud and works as a data management and storage center, while the AIoT subsystem collects data from the athlete. We then discuss experiments conducted on trainees in an AIoT environment with BMLT equipment. Biochemical data were measured to correlate the continuous physical motions measured by our AIoT system. Data measurements include body composition, maximum muscle strength, power, speed, agility, and balance. The examined items include metabolic factors, insulin-like growth factor, and endocrine hormone factors. Muscle damage factors include creatine phosphokinase (CPK) and myoglobin, and inflammatory factors include C-reactive protein (CRP), interleukin-1 (IL-1), interleukin-6 (IL-6), and tumor necrosis factor-α (TNF-α). The measurement data serve as a labeling basis for a convolutional neural network (CNN) model training process. The CNN model inputs consist of the continuous body motion patterns monitored by a noncontact sensing modality through OpenPose.

Due to the limited label samples collected for fatigue and injury for a variety of athletic body shapes and varied characteristics via biochemical experiments, the OpenSim package was used as augmentation to generate a large number of training samples that serve for customization purposes. The different subsystems form a closed loop of detect and advise to achieve the goal of secure training for better health.

THE CHALLENGES TO ACHIEVING THE GOALS OF PRECISION SPORTS INCLUDE DATA COLLECTION, IoT ACCURACY AND USABILITY (USER EXPERIENCE), AND AI MODEL ANALYSIS AND VALIDATION.

AIoT SPORT INFORMATICS AND ANALYTICS PLATFORM

To support AIoT sports science research, an integrated platform that can effectively support sport informatics and analytics is essential. Sport informatics involves collecting, representing, consolidating, storing, and computing data. Collection can involve the capture of data from sensors or through the observation of athletes. Tools and techniques that can help with this include data visualization, predictive modeling, and machine learning. In sports, this might mean improving athlete or team performance, increasing sport participation, deepening fan engagement, or developing innovative recruitment or coaching strategies. This platform uses multimodel intelligence to make inferences of possible fatigue or injuries based on data from IoT sensors, 3D modeling tools, AI, and big data analysis.

As shown in Figure 1(a) and (b), the AIoT sports science system architecture consists of two parts: the SIAS and AIoT edge computing. The SIAS provides facilities for 1) integrating and managing high-performance cloud computing resources; 2) data collection, consolidation, and management; 3) AI and deep learning; 4) 3D modeling and simulation; and 5) a sport app.

As part of the data-handling functionality of the SIAS, a real-time data stream module provides an instant streaming service that receives incoming images or data from the AIoT edge gateway. The gateway segments the data or breaks information into smaller packets and transmits them to the cloud using the MQTT protocol.

The model store modules provide storage and management of AI models, including version management, accuracy analysis, and model delivery. The data pipeline management module provides dataflow management that can be used to develop various processing pipelines based on data type or business needs. The pipeline integrates the functions of these modules, including data receiving, storage, and processing and model storage and modeling. With the pipeline's automation engine, these steps can be done in parallel.

The big data management module offers cloud management services utilizing multiple open source data storage systems, such as MongoDB, Elasticsearch, Prometheus, and Amazon Web Services S3, and stores the received data or images with appropriate metadata mechanisms to the appropriate system.

The AI model and deep-learning modules integrate a variety of deep-learning algorithms and open source frameworks and tools, including TensorFlow, Keras, and PyTorch, that can be used for processing and learning from the data sets generated by the

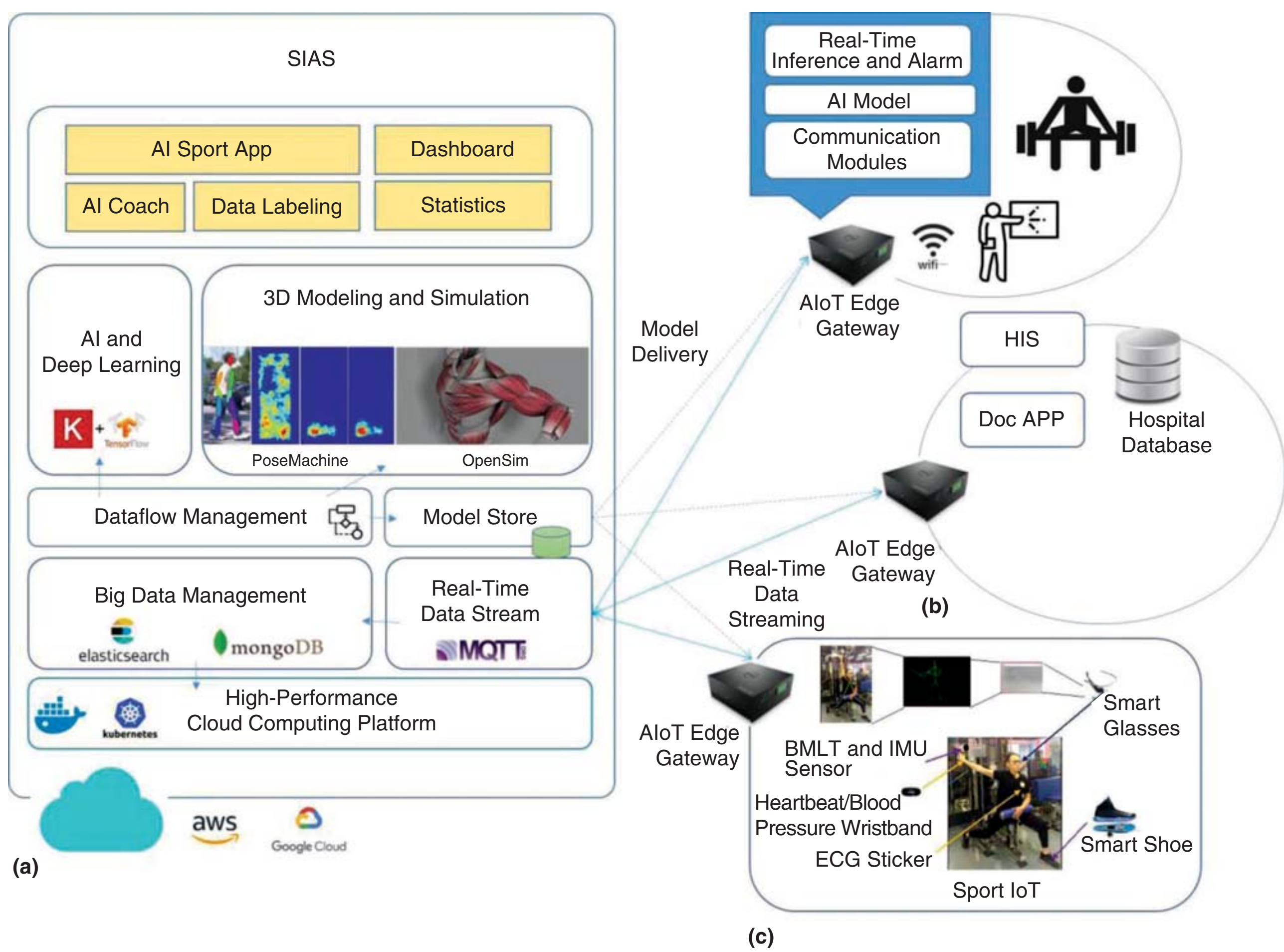

FIGURE 1. The AIoT sports science system architecture. (a) The SIAS. (b) The AIoT edge computing configuration. (c) The sport IoT system at the training equipment. HIS: health information system; IMU: inertia measurement unit; Doc: doctor.

big data management module. Various algorithms are packaged in the form of containers, and a scheduling method is employed to use the high-speed computing platform for calculation, which can be supplemented by dynamically adjusting the algorithm parameters to accelerate the model optimization.

SPORT IoT

Figure 1(c) is an illustration of sport IoT system. Trainees are equipped with a variety of IoT sensors for physiological and motion signal collection. The biological IoT sensors consist of wristbands, patches, and stickers responsible for collecting important physiological data. Motion sensors are installed on both the weight-training equipment and the trainee athlete's four limbs. Typical motion sensors include linear and angular gyro sensors that record the trainee's precise exercise stroke. A smart watch and electrocardiogram (ECG) sticker are adapted on the athlete's wrist and chest for monitoring physiological information including blood pressure, ECG signal, heartbeat, and breath rate.

The training instruction information goes hand in hand with a real-time capture of the trainee's image analyzed by OpenPose for posture analysis. A digital coach works on a synthesis for correct posture combining 3D model simulation (OpenSim). The ideal digital coach skeleton is merged with that of the trainee. A user of our system can then correct his or her motions by following those of the digital coach. Smart glasses or a big-screen TV transfers sports advice and prescriptions from the digital coach to the trainee.

3D MODELING AND SIMULATION

The development of a high-performance, motion-dynamic simulation system can assist human structural sports science. OpenSim, an open source simulation software suite, was developed in 2007 and combines the cross-disciplinary expertise of anatomy, physiology, neuroscience, kinematics, mechanics, robotics, and information science. OpenSim allows users to develop, analyze, and visualize models of the musculoskeletal system and generate dynamic simulations of movement.[5] In OpenSim, a musculoskeletal model consists of rigid body segments connected by joints. Muscles span these joints and generate forces and movement. Once a musculoskeletal model is created, OpenSim enables users to study the effects of musculoskeletal geometry, joint kinematics, and muscle-tendon properties on the forces and joint movements the muscles can produce.

The OpenSim simulator is capable of predicting and analyzing the fatigue or injury patterns on specific body parts given assigned styles of sports from a specific trainee's or user's posture data. These data can be gathered in real time from the AIoT subsystem detailed in the next section. These could include a skeleton as acquired from a standby camera and processed by the OpenPose package and more delicate data such as acceleration in both linear and angular directions. These serve as inputs to the OpenSim software for analyzing

THE BIOLOGICAL IoT SENSORS CONSIST OF WRISTBANDS, PATCHES, AND STICKERS RESPONSIBLE FOR COLLECTING IMPORTANT PHYSIOLOGICAL DATA.

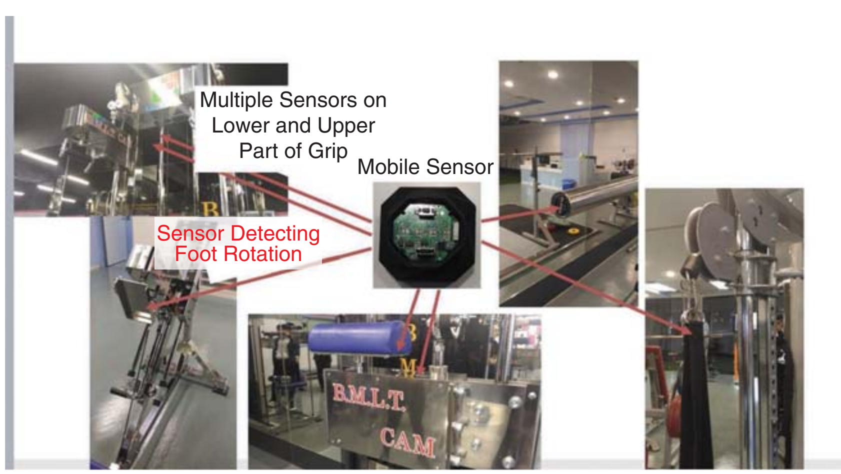

FIGURE 2. The mobile sensors mounted on BMLT devices.

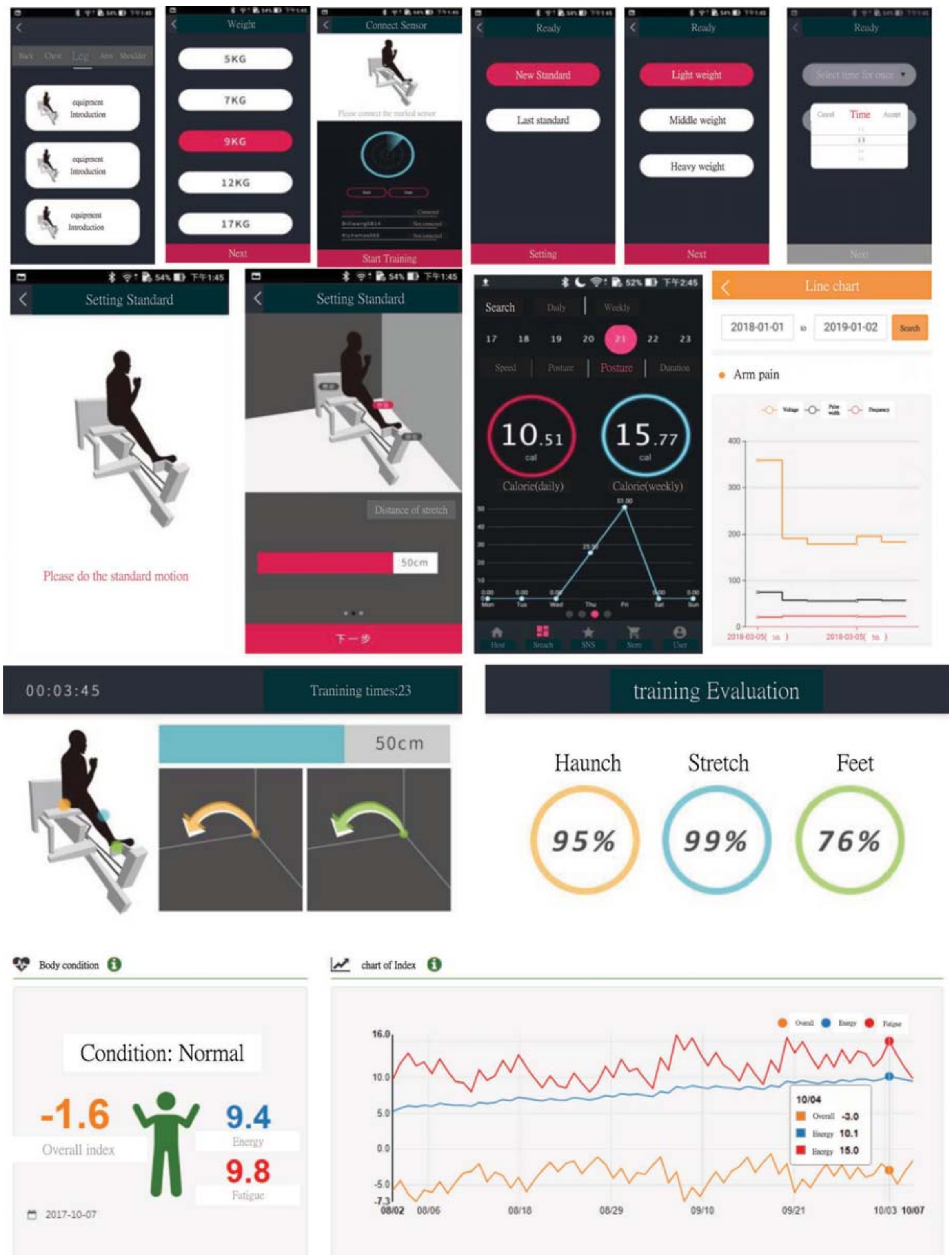

FIGURE 3. The interfaces of the app that supports BMLT.

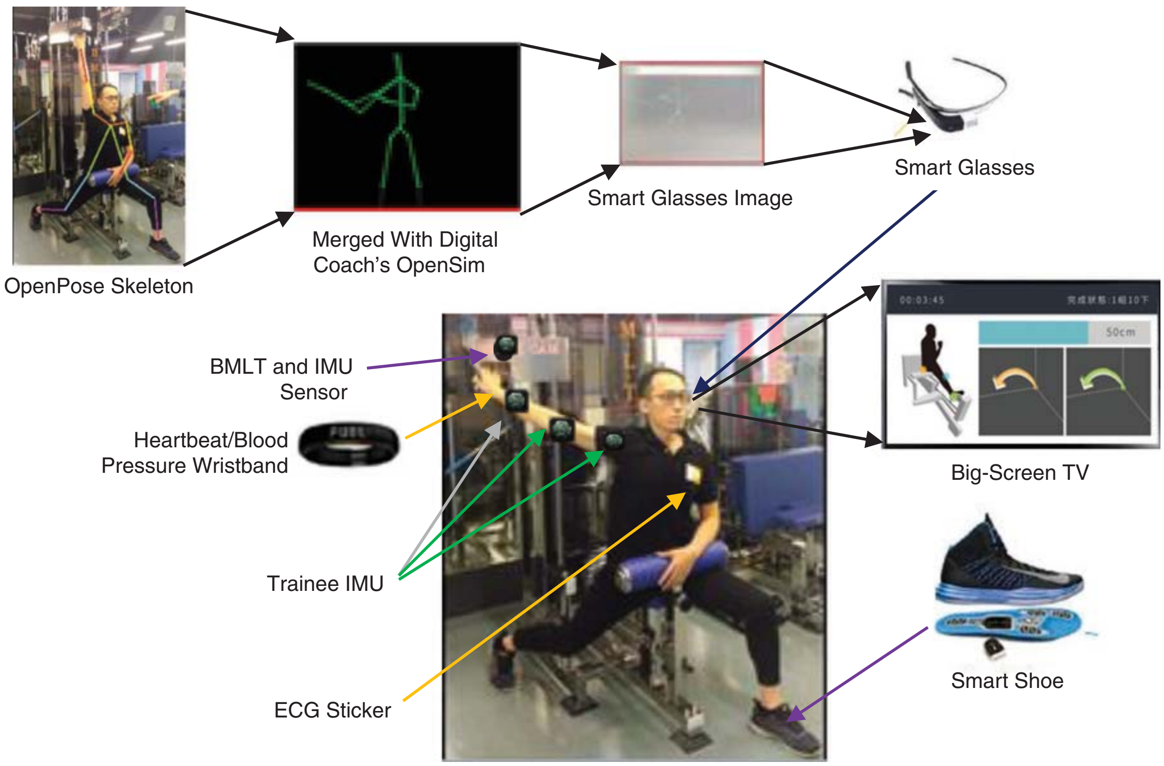

FIGURE 4. The AIoT coach formation for BMLT.

possible fatigue and injury prediction. A suggested correct motion or posture sequence can be synthesized in real time or extracted from a database where a large number of pretrained or preanalyzed motion strokes are stored. Given the real-time skeleton of the trainee acquired from the AIoT system, the back-end cloud system is responsible for merging the ideal skeleton with that of the real-time user. The merging style can have many options. Depending on the user's needs or coach's instructions, the merge can be assigned to a specific body part and provide a target for the system user to follow. Such follow-through actions allow a user to not only exercise the required stroke but also prevent injury due to over training.

EXPERIMENTS

We conducted an experiment applying AIoT to a non-AIoT weight-training set, that is, BMLT, to demonstrate its feasibility for sports science. There are many factors that affect health and sports performance. This experiment periodically collected data related to body composition, maximum muscle strength, power, speed, agility, and balance to accurately analyze and predict training factors that cause fatigue and injury. AIoT hardware was first set up on both the BMLT equipment and the athletes. Biological and chemical experiments were conducted to correlate the athletes' physiological condition with the stroke motions utilizing both traditional weight lifting and BMLT in general. The experiment was designed to introduce both the application of the AIoT setup on the BMLT equipment and the biochemical measurements related to the user motion on the BMLT.

The goal of the experiment was to show how the AIoT sport platform integrates with nondigitized BMLT equipment. Figure 2 depicts the IoT sensors mounted on BMLT devices. BMLT is designed to train various muscle groups, such as upper limbs, hips, and lower limbs.

As shown in Figure 3, an app was designed to allow users to select the training target and training strength. Before users start BMLT training, they employ the app to set options about the part of the body to be trained, weight, time of training, and class of training. After training, the analysis details and evaluation can be

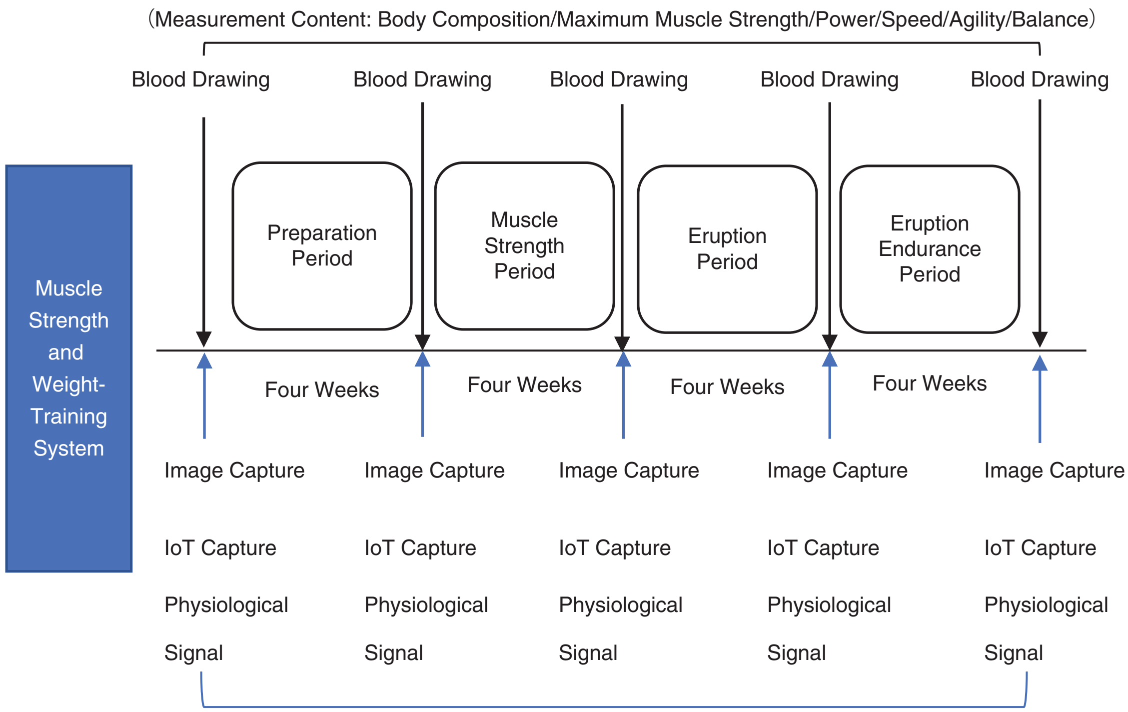

FIGURE 5. A timeline of the physiological data collection experiments relating to both image and IoT data capture setup.

provided to users in the app. It works with the AI deep-learning and data-processing modules on the cloud server to generate proper instructions for the trainee in the form of a digital coach.

Accelerator sensors of different scales, dimensions, and directions were mounted on both the BMLT equipment and relevant body parts of the trainees. Additionally, the trainees were equipped with a variety of other sensors, including heart-rate monitor, blood pressure bracelet, ECG muscle patch, myoelectric patch, and smart shoes for physiological signal collection. When incorrect movements or actions were detected or sensed by the system, the trainee was notified of the correct movements through the smart glasses and big-screen TV, as shown in Figure 4. We displayed the ideal digital coach skeleton with that of the trainee. Trainees could then correct their motions by following those of the digital coach.

The composite screens in both the smart glasses and big-screen TV provided user-friendly options from which the trainee could choose. The rotation motion was not easy for OpenPose to detect. We complemented this with motion sensors placed on specific locations on the trainee's arms and legs.

The evaluation process was performed over a period of four months, with a physical examination, joint activity measurement, and sports injury assessment and diagnosis performed every four weeks. The monthly joint activity was based on the active and inactive ranges of the main joints, including the upper limb shoulder joint (front curve/extension, abduction/adduction, 0° abduction outside/inward rotation, and 90° outreach/inward rotation), upper limb elbow joint (bending/extension and pronation/spinning), and lower limb hip joint (buckling/stretching, abduction/adduction, and hip and knee 90° flexion outside/inward rotation).

Once a scientific examination revealed a suspected injury, the diagnosis was further confirmed by X-ray, ultrasound, or magnetic resonance imaging, and follow-up treatment was provided for further improvement. Biochemical tests were given every three months. The project was divided into metabolic factors (insulin-like growth factor 1 and insulin-like growth factor-binding protein 3), endocrine hormone factors (adrenocorticotropic hormone, cortisol, and testosterone), muscle damage factors (CPK and myoglobin), and inflammatory factors (CRP, IL-1, IL-6, and TNF-α), which required a total of 10 mL of blood collection each time.

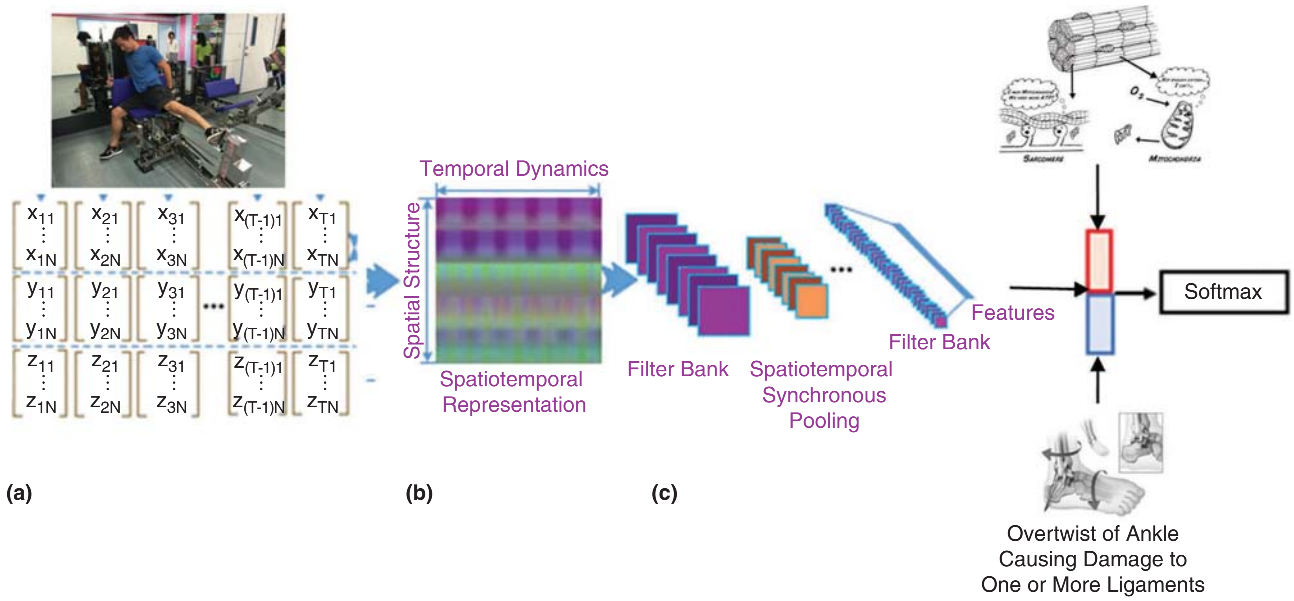

FIGURE 6. The process for CNN training and fatigue pattern labeling. (a) A matrix of values recorded from the joint coordinates forming the skeleton structure. (b) A spatiotemporal image matrix from a sequence of motion over a training period. (c) The resulting softmax weighting matrix after pooling with the CNN.

The data were collected at five intervention points, as illustrated in Figure 5, including the data collected before and after each four-week training period. The collected data included a fatigue questionnaire, heart rate, serum ketone/cortisol ratio, serum creatine kinase, blood lactic acid, blood urea, bicarbonate, blood pH, serum protein value, blood miRNA, and salivary immune protein. At the same time, high-speed cameras captured the trainee's real-time motion, which served as the input to OpenPose to generate the trainee's skeleton data model. At each moment of a training session, the OpenPose analysis generated the 21 joint coordinates forming the skeleton structure.

The coordinate values were normalized to within 0–255 along all three axes, forming a 21×3 row size image values, as observed in Figure 6(a). By recording a sequence of motion over a training period, the stacked up column of pixel values formed a spatiotemporal image matrix, as shown in Figure 6(b).

The perfusion to the spatiotemporal matrix was followed by pooling with the CNN, training with the backpropagation algorithm, and obtaining the softmax weighting matrix, as shown in Figure 6(c). In the image-recognition process, the maximum probability was used to identify the final result of the action as fatigue or injury action. The backpropagation algorithm marker can use the fatigue degree or the damage of different parts from Figure 5 as labels in the AI training process, as shown in Figure 6(c). The training result can be provided as reference for the digital coach for a warning display (feedback). As mentioned previously, the OpenSim package was used as augmentation to generate large numbers of training samples. Once the training on a large pool of samples containing both real and synthetic athletes is complete, it can serve as a source for a digital coach issuing precise, real-time sport instructions.

Traditional athletes lack efficient measures to enhance their sports performances. The practices used most often in training are manual recording and oral instructions on the athlete's exercise results while muscles are subject to harsh training cycles. The consequence is low efficiency and even secondary injuries, possibly leading to the early termination of a sports career.

Table 1 compares the features of our work with those of other relevant research. Recent research suggests that the future generation of health-monitoring devices will be a lighter weight, provide more accurate results, and easy to wear. Lee et al.[1] proposed a wearable smart shirt for monitoring physiological ECG signals and physical activity to detect abnormal events during exercises. The proposed system uses IEEE 802.15.4 for low power consumption. Sazonov et al.[2] introduced a wearable shoe-based device that has the ability to measure different postures and activities (for example, sitting, standing, walking, ascending stairs, descending stairs, and cycling). This can help people who suffer from obesity. Morris[3] proposed a pH-monitoring system using pH sensors based on collecting the amount of sweat from the patient. All three have reported the usage of body sensor networks applied to sporting events. However, no inference instrument, such as smart glasses, has been used as an advice medium for sports. Biomedical analysis based on biochemical experiments and muscle simulation via OpenSim work together to provide sport advice to an athlete in real time.

WHEN INCORRECT MOVEMENTS OR ACTIONS WERE DETECTED OR SENSED BY THE SYSTEM, THE TRAINEE WAS NOTIFIED OF THE CORRECT MOVEMENTS THROUGH THE SMART GLASSES AND BIG-SCREEN TV.

This work proposes an integral AIoT sport system architecture that contains two parts, including an SIAS and AIoT edge computing. The SIAS provides facilities for 1) integrating and managing high-performance cloud computing resources; 2) data collection, consolidation, and management; 3) AI and deep learning; and 4) 3D modeling simulation. The AIoT edge computing runs on an AIoT edge gateway and is responsible for integrating the near-end sport IoT configurations. It contains multimodal sensors mounted on both the BMLT equipment and the trainee. Both wearable and noncontact devices work hand in hand with novel IoT displays, such as smart glasses and big-screen TVs, to serve users with different needs. The sport IoT system transmits the local information to the SIAS. The system aims to serve users from a variety of backgrounds, including the amateur general public and professionals. The edge gateway can react quickly and dramatically reduce the latencies when data must be transferred to the cloud. Moreover, it works tightly with the cloud server to both gather physiological data from the trainee and coach and retrieve advice and suggestions from the AI module for the trainee. In the future, we hope to enhance the usability and satisfiability of the integral system through a usability questionnaire and the collection of a huge amount of user sensor data.

TABLE 1. A comparison of sport IoT systems.

Sport IoT research	Inference instruction	Multimodel sensing	Mathematical analysis of muscle status	Body sensor network	Biomedical analysis	Edge computing
Lee et al.[1]	×	×	×	✓	×	×
Sazonov et al.[2]	×	×	×	✓	×	×
Morris[3]	×	×	×	✓	×	×
This work	✓	✓	✓	✓	✓	✓

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