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Workload Management System for Cricketers

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***Abstract* — Cricketers are dynamic players in the field and hence more vulnerable to injuries. The injury rate of Sri Lankan cricketers is very high, resulting in their careers being shortened. Therefore, we established a workload management system for cricketers to resolve this issue with wearable Inertial Measurement Unit (IMU) sensors mounted on their bodies. In order to mitigate their accidents, we evaluated kinds of the activities performed by an athlete using Convolutional Neural Network (CNN) and computed the workload parameters after the session. The expected results of our project were to develop a system to collect and analyze the critical workload parameters of cricketers and showcase results in a user-friendly manner.**

***Keywords* — Inertial Measurement Unit (IMU), Human Activity Recognition (HAR), Convolutional Neural Network (CNN)**

I. INTRODUCTION

Cricket is a popular sport in countries like Australia, Bangladesh, England, India, New Zealand, Pakistan, South Africa, Sri Lanka, Zimbabwe and British-influenced Caribbean countries [1]. Batting, running, fielding and bowling are all highly dynamic actions. Due to this reason, cricketers are vulnerable to various physical injuries [2, 3]. According to established studies, the most common injury types are lower limb, lower back, and upper limb injuries [4, 5]. Apart from injuries, the fast bowlers are fatigued quickly due to their excessively dynamic nature [6]. Other cricketers are prone to ankle injuries [7]. Hence, managing workload is essential to minimize the injuries in cricketers.

The workload is divided into two categories; internal (physiological) and external (activity-based) [4]. The internal workload is described as a person's psychological response to the external work done by that particular person in a game, during a training session, or as everyday work [8]. Genetics, environmental conditions, biological conditions and daily life stresses not related to sports, all influence the internal workload [9, 10]. The external workload can be identified as the physical work done by the athletes, which is objectively measured, such as total time covered by sprints, number of ball deliveries and total distance during the matches, training and everyday life [4]. The external workload can be used to gather information about the work done with the athlete's capabilities and predict future training loads that can be tolerated [10]. External load is also related to the risk of the injury; if it exceeds the capacity of an athlete, it could lead to a high risk of injury [4]. Using both of these aspects in combination, the acute to chronic workload ratio (ACWR) can be calculated [11–13]. External workload is helpful to manage the risk of injury due to undertraining and over-training [8]. ACWR gives a snapshot of the preparedness of an athlete at a particular instance. For example, a low ACWR indicates under-training and therefore, the relative injury risk during a tournament is high. If the ACWR is too high, the athlete is over trained, and the risk of injury during training due to fatigue is high. If the ACWR is maintained at a proper level, we say that the athlete has reached the optimal workload and is at minimum risk for injury [14]. There are two major methods to calculate the ACWR; rolling average ACWR and exponentially weighted moving averages ACWR. We used the rolling average ACWR method for the calculations [15].

Human Activity Recognition (HAR) is a critical approach applied in different fields, including sports. Many researchers have approached this subject with various devices and algorithm combinations. One group used deep, convolutional, and recurrent methods to classify physical activities such as running and ascending stairs [16]. Another study of HAR was with smartphone sensors using deep learning neural networks, which yielded an overall accuracy of 94.79% [17]. Others proposed the use of deep recurrent neural networks (DRNN) for HAR that can capture long-range dependencies [18] and the Association for Computing Machinery in New York published a research on deep convolutional neural networks (DCNN) for HAR using wearable sensors [19]. Although the accuracy of the above study was good, with the use of inertial measurement units (IMUs), wearable sensors have become more accurate and less costly. An IMU is a type of sensor that measures angular rate, force, and magnetic field. IMUs are made up of a 3-axis accelerometer and a 3-axis gyroscope, making them a 6-axis IMU. They may also have a third 3-axis magnetometer, making the IMU a 9-axis system [20].

In this research, we developed a workload management system using IMU wearable sensors. In order to limit the scope of the research we considered a limited number of kinematic attributes and focused on quantifying 4 of the basic activities all cricketers perform during training, namely standing, walking, jogging, and running.

II. METHODOLOGY

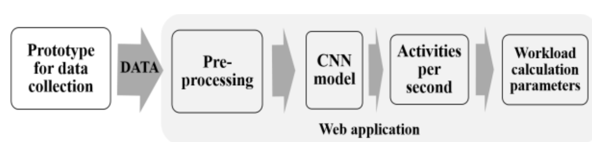

Figure 1. Block diagram of the data acquisition system; consisting of two main parts, prototype and the web application.

The procedure used for the collection, analysis, calculations and display is shown in Figure 1. Training data from subjects were stored in an SD card attached to the prototype sensor. After the training session, these data files were preprocessed offline and fed into an algorithm, which

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identified the activities during each second. The workload calculation was performed for each athlete and displayed for the coach or physician.

A. Data Collection Methods

We developed a system to collect data from three wearable IMU sensors mounted on the waist, thigh and the shank of a cricketer during the training sessions. These were attached using Velcro to the inside of pockets in the trouser worn during training. To initialize and to build up a simultaneous and synchronous connection among the three sensors, an I2C multiplexer was added to the microcontroller (ATmega328P, Arduino, Scarmagno) circuit and was powered by a 3.7 V LiPo battery. Triaxial accelerations (in ms^{-2}) were measured from each IMU and saved in the SD card adapter module (in CSV format). Data were collected at a sampling rate of 30Hz. At the end of each training session, the SD card with the data was unmounted for analysis.

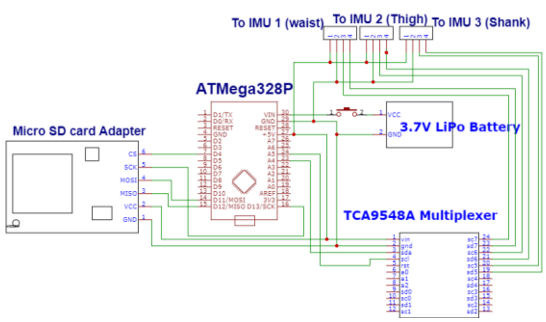

Figure 2. Circuit diagram of the prototype used to gather data. Here 9 acceleration data are taken from 3 IMU sensors (waist, thigh and shank).

Sensor drift and noise have been ignored because the data is fed directly into the neural network model, and manual filtering was not required since CNN compensates for it. Data were processed as 2D arrays of dimensions 60x9. Data for two seconds were taken as a single image. We had 6000 such labeled images. A representative image taken from the data set is shown in Figure 3. Each column of a sample is normalized and scaled to between 0 and 1 during pre-processing. In the algorithm training phase, before feeding into the algorithm, the data set was divided into training and testing sets randomly (80:20).

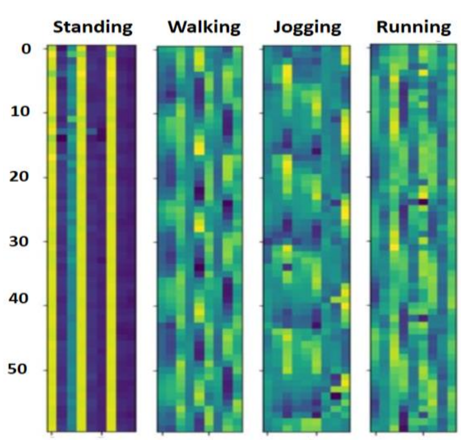

Figure 3. Representative data from each of four activities. Each sample consists of 60 time steps of 9 sensor readings (3 IMUs) for 2 seconds at a rate of 30Hz.

B. Human Activity Recognition (HAR)

HAR is applied in sports to calculate the workload of an athlete during a session, and is useful to know the activities performed and the time duration of each of the 4 activities (standing, walking, jogging, and running). The algorithm was designed to identify the activity for each second and on this basis calculate the time duration for each type of activity.

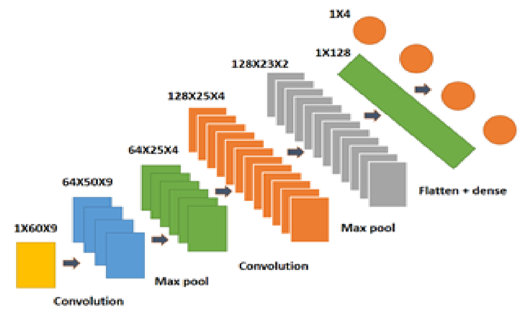

Figure 4. Visualization of the CNN architecture. How a single data sample gathered during a 2 second window goes through the CNN before recognizing the activity.

For HAR, we tested Convolutional Neural Network (CNN), Long Short Term Memory (LSTM), and a combination of both using available data. CNN outperformed the others both in accuracy and processing time and therefore CNN was selected as the preferred method for this study. We used a custom-designed neural network as shown in Figure 4 that consisted of convolution and dense layers to classify these images. In our neural network, we used two convolutional layers, each with 64 and 128 filters. We used "Dropout" layers to avoid the overfitting problem and "Maxpooling" layers to reduce dimensionality between each convolutional layer. After flattening the output from the last convolutional layers and several fully connected dense layers, we added a fully connected dense layer with four neurons as the output layer. We used the softmax activation function at the final output layer.

C. Workload Management Parameters

To calculate the workload, we considered the time the athlete covered as sprints. Then we used daily sprint times to calculate the ACWR. ACWR was calculated by dividing the past week's total workload by the average weekly workload of the four weeks preceding the past week (Eq. 1). Limits for the ACWR values are taken as; very low: ≤0.49, low: 0.5-0.99, moderate: 1.0-1.49, high: 1.5-1.99 and very high: ≥2.0 [15]. Although standing, walking and jogging are not directly taken into the account for calculation in this model, it helps to have an insight into how the practice session was conducted.

$$\mathrm{ACWR} = \frac{Total\ time\ of\ sprints\ for\ last\ 7\ days}{(Total\ time\ of\ sprints\ for\ last\ 28\ days\ prior\ to\ last\ 7\ days)/4}$$

Eq. 1

D. Web Application

In the web application, the trained CNN model was included. After the practice or match session, the CSV file consisting of gathered data was uploaded into the web application. The pre-trained CNN model made predictions which in turn was used to predict the activity performed every 2 seconds period. Thereupon, the number of minutes the athlete was standing, walking, jogging, or running and the variance of the activities with time was illustrated by the web interface. The coach or physician has an option to upload the calculated data into a database, where the workload variation during the past seven days and the variation of acute to chronic workload during the past seven days are displayed to the coach using another web interface.

III. Results

Data were collected from 1 subject (an amateur cricketer) for five sessions which lasted 40 minutes each. The first four sessions were used for training the algorithm and the final session for testing. The training session had 9744 seconds of data which translated to 4872 data samples (80% for training and 20% for validation). Data were manually labelled with the use of timestamps when collecting train and test sets.

E. Human Activity Recognition (HAR)

Figure 5 shows how the CNN algorithm classified the four different activities. According to the above results, CNN model showed an average precision, recall, and F1 score of 99.58% with an overall accuracy of 99.8%. The time taken for the processing of the model was 1.583 seconds.

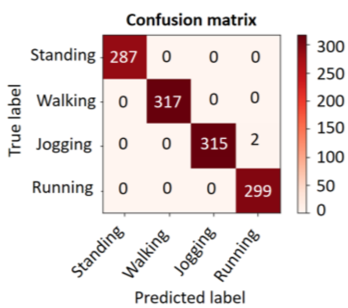

Figure 5. Results for test data taken for about 40 minutes depicted in the form of a confusion matrix for the CNN model.

F. Data Analysis and Presentation

The labels predicted from CNN architecture for each second was used to calculate the activities log for the athlete. A random data sample was taken using the prototype for about 5 minutes by an amateur cricketer, and the variation of his activities was recorded in the table as shown in Table I, and Figure 6 shows the output given by the web application when the recorded CSV file is uploaded.

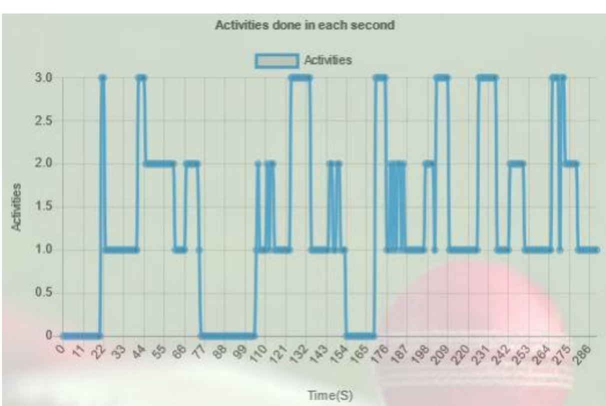

Figure 6. Web application output for the same data sample shown in Table 1. Time is in seconds, the label of each activity is shown in the y-axis of the figure; standing: 0, walking:1, jogging:2, running:3.

Table I: Random data sample taken from an amateur cricketer for 4 activities with different time slots. Time is taken in seconds and the relevant activity label is shown in the third column of the table; standing: 0, walking:1, jogging:2, running:3

Time (s)	Activity	Activity label
0-22	Standing	0
22-44	Walking	1
44-60	Jogging	2
60-66	Walking	1
66-77	Jogging	2
77-100	Standing	0
100-115	Jogging	2
115-120	Walking	1
120-135	Running	3
135-143	Walking	1
143-150	Jogging	2
150-170	Standing	0
170-176	Running	3
176-185	Jogging	2
185-196	Walking	1
196-203	Jogging	2
203-210	Running	3
210-225	Walking	1
225-235	Running	3
235-242	Walking	1
242-250	Jogging	2
250-265	Walking	1
265-270	Running	3
270-280	Jogging	2
280-290	Walking	1

The daily workload based on the running time is shown in Figure 7 (A), and the ACWR calculated for each day for a week is shown in Figure 7 (B) both the graphs are generated using dummy data to illustrate how the web application can be presented to the coaches and physicians.

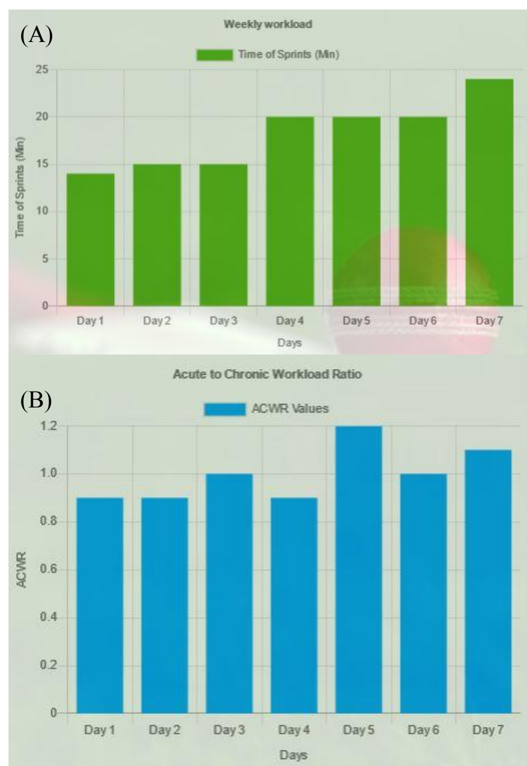

Figure 7. Web application with dummy data. (A) Weekly workload obtained from the web application, time duration of the running activity for each day is shown for the previous 7 days. (B) ACWR values for previous 7 days. This figure gives a brief understanding about what the athlete's workload is for the previous 7 days.

IV. DISCUSSION AND CONCLUSION

In this paper, we implemented a system that consisted of hardware and software components that can be used to assess and analyze the workload parameters of an athlete and enable a coach to measure long term workload in order to plan future training sessions. A prototype was developed for data acquisition, low-cost IMU sensors, which each cost approximately USD 3, were used. The overall cost consisted only of the hardware implementation (approximately USD 30) since the software tools used were open-source (Arduino and Python). The existing wearable sensor-based systems in the market typically cost more than USD 200 per sensor.

In this initial phase, we have only considered the four basic activities performed by an athlete. Typically each cricketer has a unique work load requirement, given their role in the team. For example, differentiating between different bowling actions is useful to focus purely on fast bowlers (as opposed to spin bowlers) and shoulder injuries of both types of players. However, the data for the basic activities were gathered using one of the authors (amateur cricketer). Although delayed due to current restrictions at the university due to the pandemic situation, we plan to obtain necessary approvals for testing with professional players as future work.

Further modifications can be done by replacing the existing sensors with sensors of a higher frequency, sensitivity and accuracy to classify other different activities like types of bowling among fast bowlers. For an improved activity classification and better data collection, a sampling frequency of 50-100 Hz is needed. Moreover, we hope to consider the runtime performance of the functioning of the web application as it utilizes computational power optimally.

All of the sensors were placed on the lower limb because cricketer's lower limbs are dynamic during playing. The locations for sensor placement were chosen as the combination of dynamics of these locations of the body showed the maximum variety respective to the four activities we classified. Further studies can be done on the significance of the sensor location to classification accuracy. It is possible to gather further biomechanical parameters of the lower limb with slight modifications. This system can be combined easily with an internal workload system that uses the rating of perceived exertion (RPE) and thus further customizing the training plan for each cricketer.

Since this is a low-cost system, this will be affordable for most amateur cricketers and coaches in developing countries. Furthermore, the analysis and display of results is user friendly and since it is through a web application, coaches can remotely monitor and assess the work load management of players. The development of systems such as these will popularize the concept of workload management even to amateur cricketers, enabling them to optimize their performance in an injury-free manner.

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