A Weightlifting Clean and Jerk Team Formation Model by Considering Barbell Trajectory and LSTM Neural Network

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Abstract. Clean and jerk is one category of Olympic weightlifting. The barbell trajectory including much kinematic parameters such as displacement, velocity and acceleration which provide coach and athletes to read and obtain athletes' performance. However, kinematic parameters in barbell trajectory is difficult to understand. Hence, in this paper, we propose a weightlifting Clean&Jerk performance evaluation model by utilizing neural network architecture. Considering barbell trajectory characteristics, the all kinematic parameters on trajectory are dependent and time-sequential, hence, long-short-term memory (LSTM) architecture is considered. We gather the domestic adult competitions from 2019–2021 in Taiwan and utilize video tracking scheme to obtain the barbell trajectory from Clean&Jerk competitions. From the results, our inference model archives 71% identify accuracy to indicate the performance of Clean&Jerk of the lifter. Our proposed model not only helps coaches and athletes evaluating their performance, it also shows neural network can assist sport science.

Keywords: Neural Network · Long-Short-Term memory · Weightlifting · Clean&Jerk

1 Introduction

Weightlifting is one of the focuses in Olympic game in Taiwan. Since the 2008 Summer Olympics, Taiwan's weightlifters could get many gold, silver or bronze medals in every acceding category. Taiwan's national weightlifting team has brilliant achievements, which attracted people's attention. Not only the professionals in weightlifting but also the general in Taiwan are following with interest in this program's scientific development on how to help coaches and athletes.

In daily training, coaches and athletes use mirror to adjust athletes' movement. The correct movement is important in bringing up a weightlifter. Mirror inflecting athletes' image in daily training provides real-time feedback, however, sometimes the athlete may forget their movement s in a while after finishing the practice. On the other hand, trajectory including much kinematic parameters such as displacement, velocity and acceleration provides coach and athletes to read and obtain sports' performance. Furthermore, weightlifting is a fast-paced competition. Every attempt has only two minutes. It means

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that coaches have to decide new weight for lifter's current attempt in about 30 s. It also indicates that the sport scientist should obtain opponents' performance in 30 s. To satisfy this issue, video analysis is a suit tool to obtain the sport performance for athletes and coaches to observe lifters' movement. Although video analysis efficiently provides accuracy kinematic parameters, however, the coaches or athletes should read and understand the meaning of kinematic parameters by their own experience. This may cause fault understanding the tiny difference of the kinematic parameters [1].

The barbell trajectory is a critical performance indicator to indicate Olympic weightlifter's performance since it including many kinematic parameters. Chiu *et al.* utilize trajectories to quantify successful lift's characteristics [2]. Nego *et al.* utilize trajectories to indicate the snatch movement successful of excellent male lifters in IWF (International Weightlifting Federation) World Championship and IWF Junior World Championship [3]. Barbell trajectory implies many important kinematic parameters such as barbell's displacement, velocity and acceleration provides to let coaches and athletes to indicate their sport's performance.

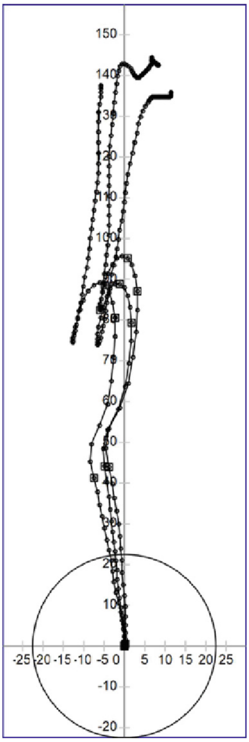


Fig. 1. Trajectories of three continues attempts

As can be seen in Fig. 1 we compare barbell trajectories of three different attempt of a lifter with three different weights on the bar. From this figure, we can observe that the three trajectories are similar. It represents that the lift performance is well down. As mentioned above, if coaches or athletes need to understand the meaning of kinematic parameters, it may need sport scientists to translate to coaches and athletes.

Kinematic parameters have been thoroughly researched in sports biomechanics and acceptably applied for sports performance evaluation. Motion Analysis system is one of popular kinematic analysis software to obtain the barbell trajectory. Not only Motion Analysis, there are also many software tools, such as Kinovea, which can obtain barbell trajectories from video sequences. However, the common problem with these software tools is difficultly operating and further consumes huge time by manual. Furthermore, after obtaining barbell trajectory, the kinematic parameters of barbell trajectory are also need experts to understand and translate to athletes or coaches.

Not only video sequence can obtain barbell trajectory, sensors are also good tools which provide high accuracy and high efficiency kinematic parameters. Sato *et al.* utilize the accelerometer to gather the trajectories of the barbell. However, when the weightlifter drops down the barbell after finishing the action, it can get a total weight is nearly 170G [1]. The sensor might be damaged. Sensors maybe easier operation then video analysis software, however, sensors cannot be suitable for the real competition. Non-contactable video analysis method for barbell trajectory gathering is the best way.

On the other hand, artificial intelligence (AI) applies in sport science in nowadays. Fialho *et al.* and Oluebube *et al.* consider AI to help people to solve mega-scale data analysis. They create and training AI model to predict the battle result in Premier League [4, 5]. Huang *et al.* and Chen *et al.* predict the NBA (National Basketball Association) team's total score and personal score in each games by considering official record information [6, 7]. Recurrent Neural Network (RNN) is one category of AI which good for handling time series material. These models not only decide the problem of weight exponential explosion, and it is difficult to capture long-term time correlation, but also archives excellent time series performance [8]. Thus, many pre-trained RNN models such as long-short-term memory (LSTM) provides time series material architecture [8].

In this paper, we create a high accuracy AI weightlifting movement evaluation model by considering barbell trajectory from video sequence. This model indicates lifters' performance not only in daily training but also for a real competition in real time. Considering the characteristics of barbell, we assume all movement information of the barbell is time-dependent. It means that any two movement points are interdependent. Therefore, LSTM architecture is chosen in our paper.

The rest of this paper is organized as follows. Section 2 introduces our LSTM model. The experimental result is discussed in Sect. 3. Discussion and conclusion result will then be shown in Sect. 4 and Sect. 5, respectively.

2 Materials and Methods

2.1 Motion Phase of Clean and Jerk

According to International Weightlifting Federation Technical and Competition Rules and Regulations, Olympic weightlifting can be divided into Snatch and Clean&Jerk categories [9]. In this paper, Clean&Jerk are considered to build the model to automatically evaluate lifters' movement. Our proposed Clean&Jerk movement evaluation model is aim to provide a high accuracy Clean&Jerk movement evaluation model for coaches and athletes to indicate the lifters' performance. Furthermore, we also like to provide an application of AI in sport science.

Both Snatch and Clean&Jerk are complex systemic movements and have high-strength muscular contractions. Lifters achieve more power outputs than other athletes [10]. Different from Snatch, Clean&Jerk is combined of clean followed by jerk. Refer to Storey *et al.*, the authors consider characteristics of Clean&Jerk and separate into twelve phases [11]. Figure 2 and Fig. 3 show each phase for clean and jerk respectively.

The motion phases are described as follows:

1. First Pull: Lifter raises up the barbell to the knee from the floor, as shown in Fig. 2 (a) and Fig. 2 (b).
2. Transition: The barbell is raised from the knee to hip joint, as shown in Fig. 2 (b) and Fig. 2 (c).
3. Second Pull: Lifter raises the barbell to the farthest with the body from the hip joint, as shown in Fig. 2 (c) and Fig. 2 (d).
4. Turnover: The barbell is lifted to the maximum vertical height from the farthest with the body, as shown in Fig. 2 (d) and Fig. 2 (e).
5. Catch: Lift catches the barbell from the maximum vertical height, as shown in Fig. 2 (e) and Fig. 2 (f).
6. Recovery from the Clean: The barbell is at the lowest position. Lifter stands up after catching the barbell, as shown in Fig. 2 (f) and Fig. 2 (g).
7. Start position for the Jerk: Lifter keeps legs straight and tiptoes parallel, and rests the barbell on lifter's collarbone, as shown in Fig. 3 (a).
8. Jerk Dip: Lifter starts squatting to the lowest position quickly, as shown in Fig. 3 (b) and Fig. 3 (c)
9. Jerk Drive: Lifter put his/her legs forth strength from the lowest position and keep legs straight finally, as shown in Fig. 3 (c) and Fig. 3 (d).
10. Unsupported split under the bar: Lifter powerfully raises the barbell to the highest position and keeps legs straight, as shown in Fig. 3 (d) and Fig. 3 (e).
11. Supported split under the bar: Lifter splits his/her legs and keeps the barbell at the highest position, as shown Fig. 3 (e) and Fig. 3 (f).
12. Recovery from the jerk: Lifter recover his/her legs to straight and parallel. Furthermore, lifter's arms should always keep straight to finish, as shown in Fig. 3 (f) and Fig. 3 (g).

The phases mentioned above split continuous trajectory. These phases make scholars easily to gather kinematic information. From relevant research of Clean&Jerk by motion phase, scholars obtain many kinematics parameters that can efficiently indicate the sports performance of the lifter [3, 12–14].

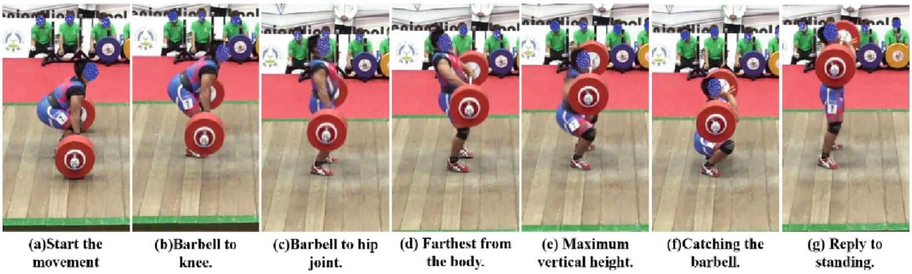


Fig. 2. Motion phase of Clean

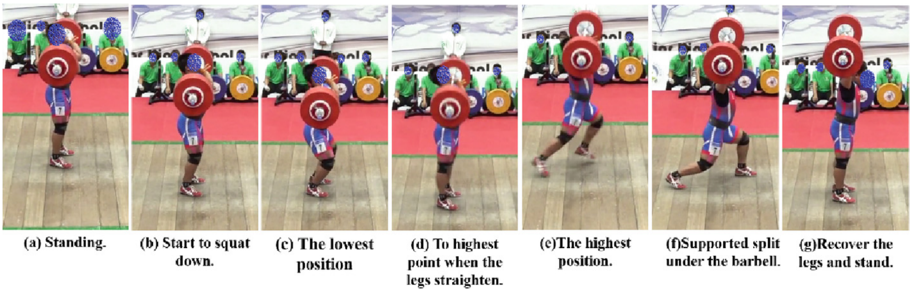


Fig. 3. Motion phase of Jerk

2.2 Experimental Procedure

In this paper, we create an AI model to evaluate the lifters' sports performance automatically. Our proposed AI model is shown in Fig. 4. In our proposed AI model, video sequence will be input and further extracted the barbell trajectory from each frame by data processing phase. In data processing phase, image pre-processing reduces the noise and blur each frame. The "classification of technical indicators" extracts barbell trajectory from video sequence and further calculate kinematic parameters of each movement phases which denotes in from the barbell trajectory [11]. The kinematic parameters are horizontal displacement and vertical displacement considered in this paper. Since movement evaluation should be in high accuracy, supervisor learning is considered in our proposed model. After kinematic parameters are gathered, the kinematic parameters will then be labeled by data labels which indicates the performance of each movement. All the video samples are randomly separated into training, validation and testing sets with 80%, 10% and 10%, respectively. Training and validation samples are utilized for neural network model training, and testing sample is used to evaluate the performance of our proposed model. We will adjust the parameters of neural network by training and validation samples, both of training lost and validation lost are considered to further provide a high accuracy model.

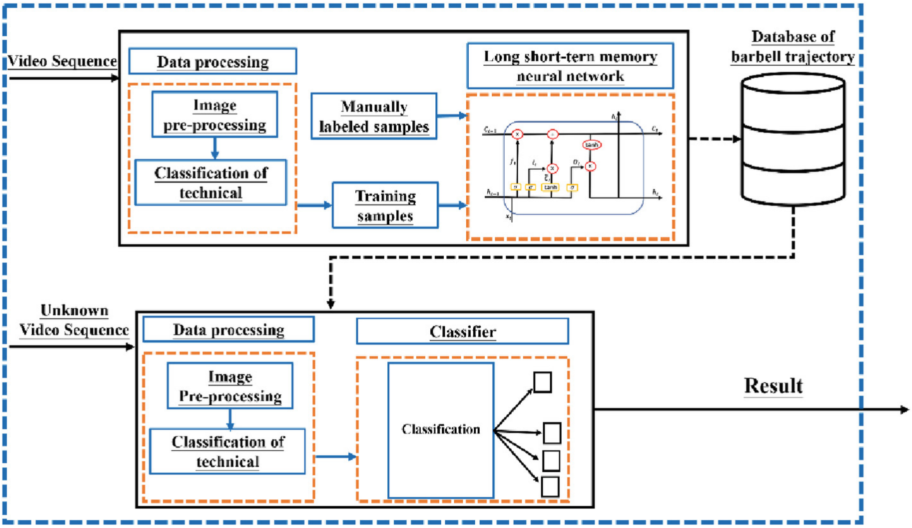
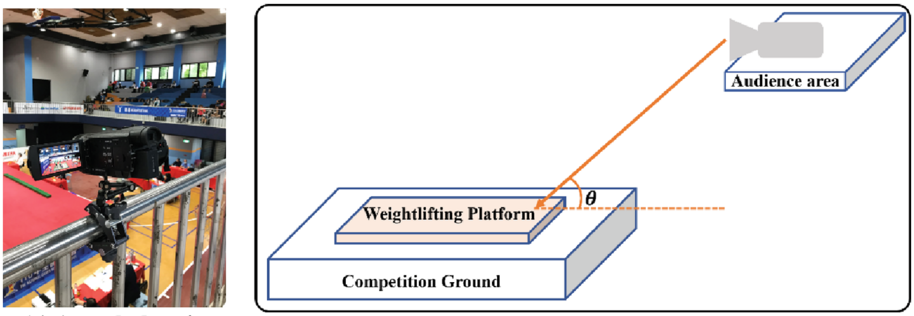


Fig. 4. Experimental procedure

2.3 Data Collection and Processing

All the video samples are gathered from Taiwan domestic adult competitions from 2019 to 2021. We select the men's 61 kg, 67 kg, 73 kg, 81 kg, 89 kg and 96 kg categories. As can be seen in Fig. 5(a), we installed the cameras in the spectator area for not affecting the game's progress. In addition, the camera is parallel to the weightlifting platform based on the collection principle by kinematics parameter. Since it is erected above the second floor, chose a nearly vertical direction to shoot, and the θ in the Fig. 5 (b) tends to be 45°.



(a) Actual place in the contest.

(b) Camera placement in the contest.

Fig. 5. Instructions figure of data collection

After collecting the video sequences, we clip and obtain the barbell trajectory. The duration of the clipped video sequence is from barbell lift-up to dropped. In this paper, barbell trajectory will be obtained from clipped by our previous work [15]. Figure 6 shows the finale of this software's automatic tracking of barbells. The kinematic parameters, horizontal and vertical displacement, will then be calculated by excel after barbell trajectory obtained.

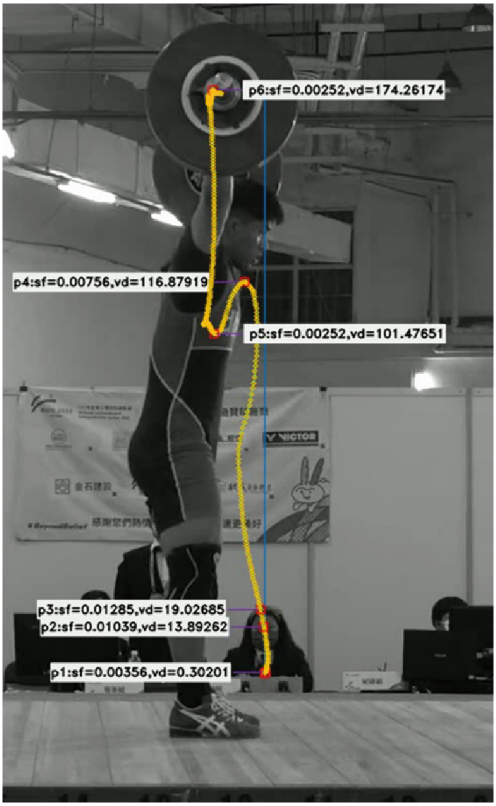


Fig. 6. Completed analysis by tracking the barbell

2.4 Neural Network Training and Parameter Adjustment

In this paper, the built-in LSTM model within Keras and Tensorflow is considered. We use Anaconda 3 to train our LSTM model and adjust the model parameters. The exhaustive of LSTM's architecture is as shown in Fig. 7. LSTM is composed of interconnected repeating units, and the internal unit design consists of four layers of logic functions (yellow rectangles in Fig. 7). One of the core concepts of LSTM is regulation through the gate (red circle in Fig. 7).

The first step is to decide which information to forget. Through the logic function, we can determine the proportion of the information brought in from the output of the

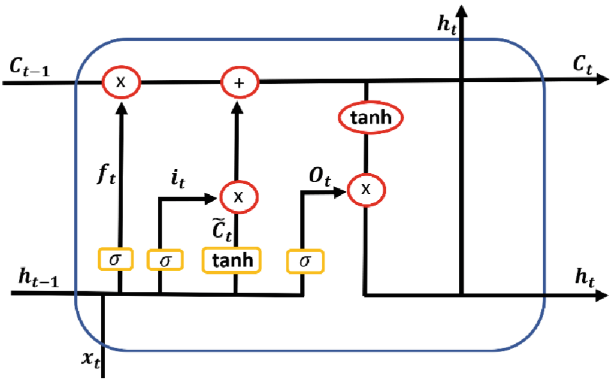


Fig. 7. LSTM neural network's architecture.

previous layer and the newly added input of this layer to be forgotten and not brought into the next layer (as can be seen in Fig. 8 (a)). The equation is shown in (1) as follows.

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

The next step is to record the newly brought-in data into the central unit state. There are two steps: deciding what to record and updating the unit. Equations (2)–(4) and Fig. 8 (b)–(c) determine how much new information needs to be registered. Then the activation function (*tanh* function taken as example) calculates a vector to determine how much information C_t need to update the central unit.

$$i_t = \sigma\left(W_i \cdot \left[h_{t-1}, x_t\right] + b_i\right) \tag{2}$$

$$\widetilde{C}_t = tanh\left(W_c \cdot \left[h_{t-1}, x_t\right] + b_c\right) \tag{3}$$

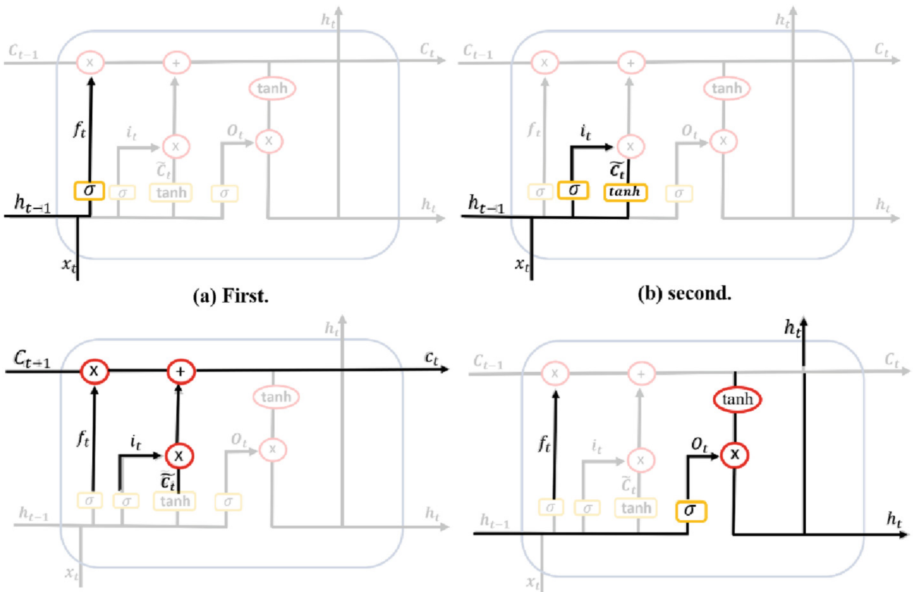
$$C_t = f_t \cdot C_{t-1} + i_t \cdot \widetilde{C}_t \tag{4}$$

Finally, we decide how much information to output as Eqs. (5)–(6). From the result C_t of the previous step and the f_t by the forgetting measure, through the control of the logic function and *tanh*, it is determined that the central unit is to be output, such as shown in Fig. 8 (d).

$$O_t = \sigma\left(W_o \cdot \left[h_{t-1}, x_t\right] + b_o\right) \tag{5}$$

$$h_t = O_t \cdot tanh(C_t) \tag{6}$$

After LSTM model created, the model parameters such as numbers of neural, activation function, training times and data amount should be decided by each training. The model parameters will be shown as follows.



(a) First. (b) second. (c) Third. (d) Fourth.

Fig. 8. Standard LSTM do at each step in the unit.

3 Result

In this paper, we only focus on good lift, therefore, totally 149 Clean&Jerk barbell trajectory with 2980 kinematic parameters are gathered. We labeled the barbell trajectory by considering the ranking of the Clean&Jerk competitions. The barbell trajectory of first three grade will be labeled as well-lift, otherwise will be normal-lift. The experimental results are shown in Table 1. Our proposed the model parameters of proposed LSTM weightlifting barbell trajectory performance evaluation model are decided by both considering training loss rate and validation loss rate. Our proposed model archives 71% for both accuracy and precision and recall rate is 59%. Table 2 is confusion matrix to present the sensitivity of our proposed model.

Table 1. Model performance index

	Value (%)
Accuracy rate	71%
Precision rate	71%
Recall	50%

Figure 9 shows the finale of the neural network's composition. As can be seen in Fig. 9, we have a LSTM with 64 output nodes connected by a dense layer as output with

Table 2. Confusion matrix

		Predict class	
		True	False
True class	True	71.4%	71.4%
	False	28.6%	28.6%

```
Model: "sequential_7"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_7 (LSTM)               (None, 64)                16896

 dense_7 (Dense)             (None, 2)                 130

=================================================================
Total params: 17,026
Trainable params: 17,026
Non-trainable params: 0
```

Fig. 9. The final result of the neural network after adjustment.

2 output nodes. All of the parameters in each layer are shown in Table 3. Furthermore, we also revise the learning rate, epoch, and batch size to 0.00001, 2000, 10, respectively.

Table 3. Relevant adjustment parameters of each layer.

layer	Activation function	units
LSTM	Softsign	64
Dense	Softmax	2

4 Discussion

From the experimental results shown in Table 1, we can observe that our proposed LSTM weightlifting barbell trajectory performance evaluation model indicates the lifters' performance in high accuracy. Both referring to Table 1 and Table 2, our proposed model can archive accuracy and sensitivity. The proposed model provides lifters, coaches and sport scientists an efficient way to help the lifter to improve his/her skill. Lifters, coaches or sports scientists use a camera to capture the lifter's attempt video, and then the barbell kinematic parameters are obtained to evaluate this lifter's performance and technology quickly. This improvement reduces the operation procedure and efficiently utilizes sports biomechanics in daily training. The result of this model also can efficiently indicate the sport performance of the lifters [3, 16–18].

Weightlifting is a competitive sport that needs powerful muscle and excellent technique for a good lift attempt. As mentioned, observation kinematic parameters of barbell trajectory although can be gathered, however, the meaning of the kinematic parameters may need sport scientist translated to lifters and coaches. Otherwise, coaches and lifters may obtain the gesture with their eyes and their experience. From our LSTM weightlifting barbell trajectory performance evaluation model, the kinematic parameters from video sequence will be further evaluated to indicate lifter's performance in high accuracy. It shows that machine learning can be suit for sport data classification to further assist coaches or athletes in daily training course and competition information gathering.

5 Conclusion

An LSTM weightlifting barbell trajectory performance evaluation model is proposed in this paper. The result shows our proposed model both archiving efficiency and accuracy. This model provides evaluation of the lifters' performance of Clean&Jerk by considering kinematic parameters of barbell trajectory to lifters, coaches and sports scientists for adjusting the gesture and further deciding the tactic in competition. We can conclude that our proposed model not only provides an efficient and easy tool for kinematic analysis and further indicate that machine learning technique can be suited for sport science.

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