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Badminton Activity Recognition and Player Assessment based on Motion Signals using Deep Residual Network

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***Abstract*—With the fast expansion of digital technologies and sporting events, interpreting sports data has become an immensely complicated endeavor. Internet-sourced sports big data exhibit a significant development trend. Big data in sports offer a wealth of information on sportspeople, coaching, athletics, swimming, and badminton. Today, various sports data are freely accessible, and incredible data analysis tools based on wearable sensors have been established, allowing us to investigate the usefulness of these data thoroughly. In this research, we investigate the detection of badminton action and player evaluation based on movement data captured by wearable sensors. Movement data captured by an accelerometer, gyroscope, and magnetometer are utilized for training and validating a classification model for badminton actions. In addition, the movement signals are used to train a player evaluation model employing a deep residual network. To assess our suggested technique, we utilized a publicly available benchmark dataset consisting of inertial measurement unit (IMU) sensors attached to every investigator's dominant wrist, palm, and both legs. The experimental findings indicate that the proposed deep residual network obtained good performance with a maximum accuracy of 98.00% for identifying badminton activities and 98.56% for evaluating badminton players.**

***Keywords*—badminton activity recognition, stroke classification, player assessment, wearable sensors, deep residual network**

I. Introduction

In recent years, human activity recognition (HAR) with wearable appliances has cleared the way for emerging technology possibilities, particularly in competition-related fields [1], [2]. Especially in the context, accessibility, and affordability of such wearable gadgets on the market, it is conceivable for ordinary individuals to acquire and utilize such technologies. The demand for these appliances and recent advancements in machine learning could assist their usage in various industries, including wellness monitoring and exercise, sports actionable insights, labor force monitoring and reporting, and many more [3], [4]. Exercise analytics is a burgeoning discipline that is achieving worldwide recognition. For almost all sports, amateurs and professional athletes depend on the analytics team to enhance their talents, evaluate their competitors, and devise winning tactics. Badminton is one of these competitive and strategic sports that may be considerably enhanced with analytics.

Badminton is a sport that places a significant emphasis on strategy, skill, and the actual performance of motions. Players and coaches are engaged in inexpensive and small sensor technology that can record the essential measures to acquire pertinent, meaningful data.

Most practice and competition evaluations are performed manually by coaches or spectators or through video-based technologies [5]. While the first demands the coach's attention and time which may not always be available, and the second involves evaluating time, high implementation costs, resolution challenges, and privacy concerns, the coach is still optimistic about objective performance assessment [6]. A modest wearable technology accessible to all skill levels could solve these issues universally [7].

This research aims to identify badminton actions based on accelerometer, gyroscope, and magnetometer data collected from many body sites. Based on these observations, the received signals from the wearable sensors are analyzed and learned to discriminate between various activities. In addition, we are developing a model to evaluate the effectiveness of badminton players. The recommended models are based on residual networks that are capable of distinguishing complicated

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behaviors such as badminton actions in an effective manner. The following is a brief description of our constitutions:

- We propose a new technique for activity identification based on deep residual learning and employing accelerometer, gyroscope, and magnetometer data from various frame sizes.
- Based on the recommended model, we categorize six distinct badminton strokes and evaluate five player levels.

II. Related Studies

Investigators have recently issued numerous methods and frameworks for identifying human physical movement. Some systems for activity detection and monitoring rely on wearable devices [8]–[15]. This section contains a selection of relevant scholarly researches.

Currently, wearable gadgets are pretty fashionable. These instruments have accelerometers, gyroscopes, and magnetometers that are precise enough to identify everyday human actions (e.g., strolling, jogging, seating, climbing stairs) [16]–[18]. This study field is exciting since it has a broad range of possibilities. Consequently, this technique is often employed without awareness. In the previous several years, many systems for monitoring activities have emerged. For various sports, a great deal of study has previously been conducted on the approaches for identifying motion. Existing research often emphasizes coarse-grained activities or differentiates across various sports groups [19]. In terms of motions and strokes, tennis is one of the sports that resembles badminton the most. Although the strokes are executed separately, the fundamentals behind action recognition are comparable. In this manner, one might train new models that are defined for unexplored motions. In order to further enhance the outcomes, a deeper understanding of the particular sport/movements is necessary [20], [21].

Unfortunately, the listed research does not necessarily go further into a vast array of motions. In [22], coarse-grained activities (strolling, jogging, sleeping, etc.) are identified, while [23] investigates the distinction between a service and a non-service. Typically, the number of detected strokes is limited, and the focus is entirely on producing a solution that works without investigating which factors influence performance. The study [7] is equivalent to our work on strokes and technique, despite the less user-friendly sensor location and the identification of just five activities. Due to the use of a novel neural network structure (ensemble learning based on separate timescales), the accuracy of our study has increased from 88.9% to 99%. In [24], a convolutional neural network can recognize tennis strokes with up to 96.5% accuracy. Finally, Rahmad et al. [25] use a CNN again, but this time using visual recognition, achieving an accuracy of about 98.7%.

III. Proposed Methodology

The proposed sensor-based HAR methodology composes of four main processes: data acquisition, data pre-processing, data generation, and model training and evaluation, as indicated in Fig 1.

A. BAR Dataset

Four wearable Shimmer units were utilized in the BAR dataset [26]. Shimmering instruments include 3-axis sensors of a low noise accelerometer, a high noise accelerometer, a gyroscope, and a magnetometer. In this collection, each individual's dominant wrist and palm, including the left and right leg, were fitted with four sensors to record the motions for each stroke. The racket's weight was roughly 75 grams, whereas the sensor's weight ranged between 23 and 30 grams. The dataset acquired 30 repetitions (12 strokes details in Table I) from the three male subjects of 27 average age. Although the description of the postures in Table I might have seemed ambiguous, all players used standard strokes and stances. The researchers of [26] determined the dataset's label. Each action's beginning and ending times were recorded throughout data collection, and a label was given based on this information. In addition, we used a camera to capture the data gathering procedure to enhance the labeling. We believe there could be an error at the beginning and conclusion of each activity using this method of label assignment; nevertheless, because the sampling rate was 512 Hz, the mistake could be tiny and not influence the classification work. For player evaluation, they were coupled with points connected with each stroke and posture executed by the performer, as indicated in Table II.

TABLE I
Detailed explanation of the strokes and stances taken into account for this research

Label	Racket Position	Stroke	Stance
1	Forehand	Service	Subtle leg movement
2	Backhand		
3	Forehand	Clear Lob Overhead	Step back with a slight jump
4	Backhand		
5	Forehand	Clear Lob Underhead	Step sideways
6	Backhand		
7	Forehand	Net Shot Underarm	Lunge like forward steps
8	Backhand		
9	Forehand	Drop Shot Overhead	Stand and deliver or slight jump
10	Backhand		
11	Forehand	Smash Overhead	Weighty movements and jumps
12	Backhand		

TABLE II
Score sheet for player evaluation

Score	Stance and Footwork
0	Incorrect stance and stroke performance
1	Played the stroke accurately but not performed the required stance
2	Using the proper stance while making the stroke
3	Continuation after the stroke performed
4	Appropriate stance and stroke performance

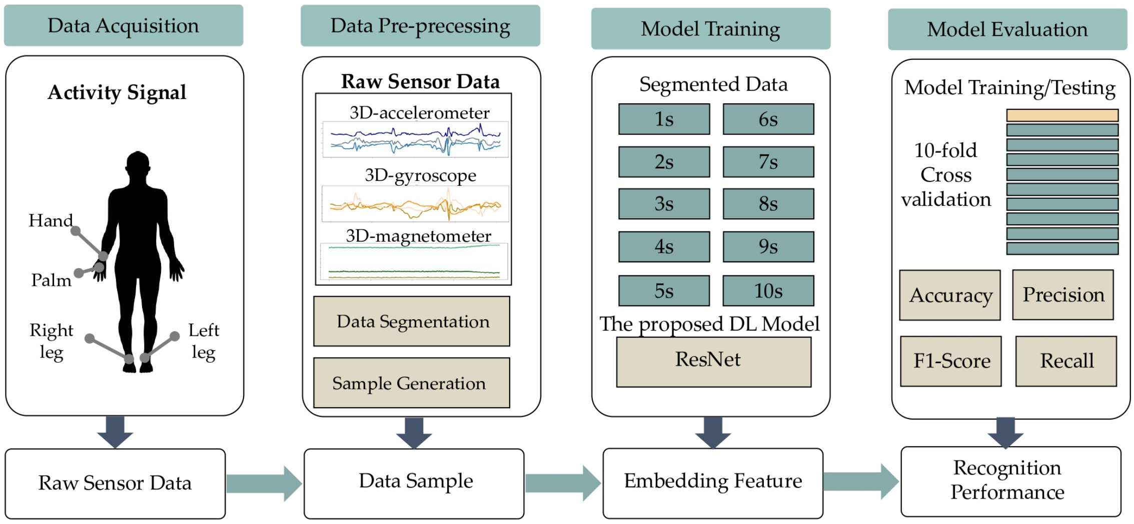

Fig. 1. The sensor-based methodology based on smartwatch sensors used in this work.

B. Data Pre-processing

The relevant adjustments were performed to the raw sensor data during data pre-processing:

- The noise is reduced by using both median and third-order low-pass Butterworth filters with a 20 Hz cutoff rate.
- Normalization of data is performed by employing the Min-Max technique.

The pre-processed sensor data were then partitioned using sliding windows with preset widths ranging from 1 to 10 seconds, with the degree of overlap determined by the 1-second step size.

C. Proposed ResNet Model

This research showed a CNN-based deep learning algorithm for sensor-based HAR detection. ResNet is the name of the proposed DL model that uses convolutional layers and residual connections to extract features proactively. Applying a Batch-Normalization (BN) layer and a ReLU layer to this network improved its detection capabilities by expediting network training and reducing gradient vanishing and overfitting issues, as seen in Fig. 2.

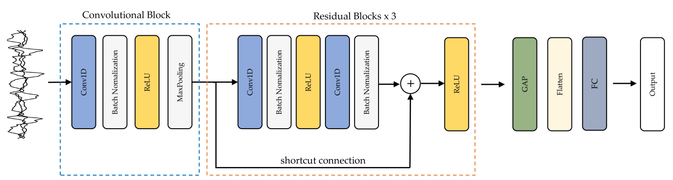

Fig. 2. The ResNet architecture.

IV. Experiments and Results

The BAR dataset was filtered and constructed using a procedure for 10-fold cross-validation. This research performed two trials to assess the ResNet model. As indicated in Table I, the first investigation was carried out to train and evaluate the ResNet for stroke identification using six badminton actions. In the second experiment, ResNet was tested to evaluate five badminton players' levels, as shown in Table II. For these two tests, we tested ten distinct window widths ranging from 1s to 10s to determine the optimal one. The experimental outcomes are summarized in Tables III and IV.

TABLE III
Effectiveness of the Proposed ResNet Model for Stroke Classification

Window	**Model Performance**		
Sizes(S)	**Accuracy**	**Loss**	**F1-score**
1	71.15%	1.75728	67.75%
2	85.88%	0.56517	83.45%
3	94.36%	0.22369	93.28%
4	95.21%	0.16414	94.40%
5	95.64%	0.15252	94.70%
6	98.00%	0.05373	97.58%
7	97.21%	0.08418	96.60%
8	97.21%	0.02436	97.05%
9	97.45%	0.0708	97.06%
10	80.97%	0.87995	76.36%

The results (in Tables III and IV) show that the proposed ResNet model reached the most satisfactory accuracy of 98.00% for stroke classification using the window size of 6s. For badminton player assessment, the ResNet model achieved the best accuracy of 98.56% using the same window size. Therefore, the sensor data segmented using the sliding window of 6s is suitable for training the proposed ResNet model.

V. Conclusion and Future Studies

This paper investigates badminton activity identification using a deep residual network known as the ResNet model. The advanced ResNet model demonstrated a high performance (above 98%) for stroke classification and player evaluation.

TABLE IV
EFFECTIVENESS OF THE PROPOSED RESNET MODEL FOR PLAYER ASSESSMENT

Window	Model Performance		
Sizes(S)	Accuracy	Loss	F1-score
1	75.83%	2.02646	64.43%
2	88.86%	0.87412	83.21%
3	93.94%	0.29835	90.62%
4	96.36%	0.17683	95.07%
5	97.95%	0.09901	97.07%
6	98.56%	0.07707	97.74%
7	98.20%	0.03041	98.40%
8	97.80%	0.08388	96.46%
9	80.97%	0.87995	76.36%
10	79.39%	1.02179	79.04%

We investigate the optimal window size and determine that 6s-segmented sensor data is optimal for training the proposed ResNet.

A future study might also involve the assessment of the suggested DL model in other datasets with a more significant number of patients exhibiting distinct sport-related features. The effectiveness of constructing more complicated and lightweight deep learning models and unique data representations based on time-frequency analysis might be enhanced.

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