Strategy analysis of badminton players using deep learning from IMU and UWB wearables

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Abstract

Badminton is a fast-paced sport that requires a high level of skill and coordination. To improve their skills, players can use activity trackers to monitor different shots and activities. These trackers utilize inertial measurement units (IMUs), which measures acceleration and angular velocity on the rackets, and the ultra-wideband (UWB) sensors, which measure the location of the player. This study first analyzes the use of UWB localization for tracking badminton players on the court and analyzes the location where shots are played. Furthermore, this study focuses on using both IMU at the racket and wrist and UWB sensors to recognize strategies utilized in badminton matches, employing convolutional neural network (CNN) and Long-Short-Term Memory (LSTM) models. The goal is to classify thirteen badminton shots, as well as an extra class that contains non-shot activities. The output of this shot classifier is provided to the strategy recognition model, which can identify four main strategies, with eleven variations in total, alongside an additional class designated for non-strategy instances such as movement or rest intervals. We trained and tested the models on data from six skilled badminton players. The best results were achieved by using both IMU and UWB data. The proposed 2D-CNN achieved a shot classification accuracy of 90.9%, while the proposed LSTM achieved a strategy recognition accuracy of 80%. The results of this study suggest that neural networks can be used to effectively classify badminton shots and strategies to improve the training of badminton players, as well as to analyze match data.

1. Introduction

Badminton is a competitive sport where players use a small, long racket to hit a shuttle over the net. It can be played with two or four players in two teams. Players always strive to improve their skills and overall game, and practicing with a trainer is one way to do so. However, trainers can be expensive and not always available for individual refinement. To address this, a virtual assistant can be utilized to analyze players' shots and movements in real-time, offering a comprehensive analysis of their playing style with both qualitative and quantitative aspects.

To analyze the shots and movements, the virtual assistant requires the player's data, which can be captured using inertial measurement units (IMUs). IMUs are small sensors that capture data types such as acceleration and gyroscope data in three different orientations. These sensors are already popular in healthcare, robotics, virtual reality, and other sports applications [1]. IMU sensors are lightweight, affordable, easy to use, and can be attached to the player's legs, arms, chests, rackets, etc., to monitor their activities accurately. Additionally, capturing the player's position on the court and movements can be used for determining their precise location, and this can be achieved through the use of ultra-wideband (UWB), a positioning system that requires anchors and a localization sensor. UWB anchors are static sensors with known positions and communicate with the localization sensor to calculate its position using the two-way-ranging (TWR) technique. The use of UWB indoor localization systems has been used to monitor the positions and movements of ice hockey [2] and tennis players [3]. In these papers, it has been shown that UWB localization systems offer precise accuracy for these applications and can maintain affordability and ease of deployment without requiring intensive calibration. Therefore, this paper also incorporates UWB to monitor the positions of badminton players.

Developing traditional rule-based algorithms for shot classification and movement prediction using IMU and UWB data can be challenging due to its complex nature. However, machine learning techniques such as convolutional neural networks (CNNs) [4] offer a potential solution. In other sports research, deep learning models are gaining prominence for their superior performance over traditional feature-based methods like Support Vector Machine (SVM), decision trees, random forests, etc., which require manual crafting of domain-specific features [5]. As such, deep learning methods such as CNNs, originally designed for image classification, are now successfully applied to sports analytics. A notable example is presented in [6], which uses CNNs to classify badminton shots based on IMU data, highlighting the effectiveness of deep learning in extracting meaningful patterns from temporally arranged data. This classification can help in automatic analysis and match processing, as well as provide insight into similarities and differences between shots and players. Similarly, recurrent neural networks have been used with great success in other problems involving time series or temporal sequences [7]. One of the most used recurrent models is the Long-Short-Term Memory (LSTM), which incorporates a set of gates that aim to maintain a stable gradient of the neural network [8]. This type of neural network has also been recently successful at sports action recognition tasks [9].

In addition to shot classification, the virtual assistant can employ a shot comparison system. For comparing shots, the objective is for players to perfect their played shots, mimicking ideal shots. Various techniques, such as Euclidean distance or mean absolute error (MAE), can be used to compare time series (cf. IMU data of different shots). In addition, autocorrelation functions can be applied to differentiate shots of the same player to assess their consistency, as well as to compare players among themselves. Using the results of the classification and analysis, players can learn from their mistakes and improve their skills. They can compare their playing style with that of professional players and make adjustments to their shots and movements without the intervention of a certified trainer.

Moving beyond individual player analysis, the automation of badminton data analysis has become increasingly popular in recent years. Top athletes often have a team of experts, including video analysts who manually analyze the footage. For these professional matches, high-end camera systems are available from multiple angles with optimal lighting conditions. To automate this process, techniques such as computer vision [10] and the use of movement sensors can contribute to recognizing and analyzing strategies. Building upon previous research [6], which classified strategies through rule-based algorithms and machine learning by localizing the opponent player, this paper extends the research by using more realistic data and comparing different machine learning techniques for classifying 13 shots (fore- and backhand serve, fore- and backhand clear, forehand smash, fore- and backhand drop, fore- and backhand lob, fore- and backhand net drop, dab and drive) and 11 strategies (2 long diagonals, 4 other corners, 4 same corners and play to the middle). A detailed description of these shots and strategies is provided in Section 3 of this paper.

The main contributions in this paper are as follows:

- In contrast to prior studies that relied on video input, we are the first to show that badminton strategies can be recognized from players who are equipped with wearables containing IMU sensors (acceleration data) and UWB radios (location data) for shot and strategy recognition.
- We compare the performance of different machine learning (ML) based frameworks capable of both shot recognition and badminton strategy recognition using both IMU and UWB-based wearables.
- Design and analysis of a ML model using LSTM that utilizes UWB data and the classification output from shot recognition. Using our approach, we are the first to recognize up to 11 frequently used badminton strategies, compared to 2 strategies from prior work.
- We provide a comprehensive dataset comprising 13 distinct shots and 11 strategies executed by six professional and semiprofessional players, and we are releasing this dataset as open-source. The dataset is the first that includes IMU and UWB location data for both players[1].

The paper is structured as follows. Section 2 presents a comprehensive overview of related work in the field of badminton shot analysis. In Section 3, we explore the experimental data collection process, specifically focusing on real badminton matches. Section 4 provides a detailed description of the proposed methodology, while Section 5 presents the results obtained. Finally, Section 6 concludes the paper and outlines future research directions.

[1] The dataset is available at https://github.com/BenVanHerbruggen/Badminton_IMU_shot_strategy_recognition.

2. Related Work

Table 1: Overview of the discussed related work for shot recognition and strategy recognition for racket sports.

Paper	Sport	Goal	Method	Sensors	Number of classes	Accuracy	Player level
[11]	Badminton	Shot and activity recognition	CNN, DNN and Ensemble learning	3 × IMU	7	98%	novice
[12]	Badminton	Shot classification	HMM	1 × IMU	10	95%	professional - amateur - novice
[13]	Badminton	Sensor system for smash analysis	Sensor Fusion	1 × IMU	1	-	-
[14]	Badminton	Returning shot and position prediction	PM and DyMF	Labels	10	-	professional
[15]	Badminton	Shot classification and Performance predictor	CNN and kNN	4 × IMU	12	89.09%	professional - amateur - novice
[6]	Badminton	Shot classification	CNN	1 × IMU	9	93.35%	novice
[16]	Tennis	Shot classification	Pan Tompkin's algorithm, DTW and QDTW	1 × IMU	6	88%	professional
[17]	Table tennis	Shot classification	PCA and SVM	3 × IMU	5	97.41%	-
[10]	Badminton	Shot and strategy classification	GMM	Vision	6 shots and 2 strategies	83.5% (shots) and 70% (strategies)	professional
This paper	**Badminton**	**Localization analysis, shot and strategy recognition**	**CNN 1D and 2D LSTM**	**UWB 1 × IMU**	**14 shots and 12 strategies**	**90.9% (shots) and 80% (strategies)**	professional - amateur

2.1. Machine learning for shot and strategy recognition

Shot recognition and analysis have been extensively explored in the field of badminton player analysis. Several approaches have been proposed to recognize and classify shots accurately.

Steels et al. [11] compared the use of DNN and CNNs for activity and shot recognition. They used three AX6 IMU sensors (arm, wrist and racket) and a simple CNN to classify the shots, achieving 98% accuracy in distinguishing seven different shots. In contrast, our research focuses on a more complex system architecture with two AX6 IMU sensors (wrist and racket), achieving a 91% accuracy in distinguishing fourteen different shot classes. Additionally, Steels et al. concatenated shots from different novice players manually without a shuttle, which differs from the realistic scenarios we consider.

Khan et al. used an improved hidden Markov model (HMM) to classify ten different shots based on one sensor at the racket [12]. Their approach achieved a high accuracy of 95% using statistical modeling instead of deep learning techniques. The data used in their study consisted of shots from fifteen players at three different levels of players.

In addition to shot recognition, shot analysis plays a crucial role in understanding the reasons for misclassified shots. Kiang et al. [13] proposed a sensor network using an accelerometer and an acoustic sensor to perform smash analysis in badminton. They quantized the shots using the accelerometer and detected the shot impact using the acoustic sensor. Furthermore, they calculated maximum acceleration and speed, employing correlation techniques for analysis.

Another direction of research focuses on the analysis of opponent shots and positions. Chang et al. [14] introduced a player movement graph and a dynamic graphs and hierarchical fusion model for movement forecasting (DyMF). Their model captures information about a player during a match, predicting the opponent's position and following shots. They differentiated ten badminton shots and evaluated their model using metrics such as mean squared error (MSE). However, they used a preexisting dataset [18] with 11 shots, which differs from our deep learning approach with 13 shots and 11 strategies.

Training models for shot recognition and analysis can improve performance and aid in player development. Ghosh et al. [15] proposed a three-piece system to assist badminton players in their training sessions. Their system classified twelve badminton shots, compared shots using metrics like MSE and MAE, and trained a CNN to predict and analyze the performance of the shots at five different levels. The predictive module achieved an accuracy of 89%. However, their hypothesis regarding the importance of lower limb data for shot performance has yet to be validated, and composing a series of only five performance classes presents challenges.

Not limited to badminton, similar sensor-based approaches have been applied to other sports. In tennis, Srivastava et al. [16] used dynamic time warping (DTW) and Quaternion Dynamic Time Warping (QDTW) with smartwatch accelerometer data to distinguish nine different shots and achieved an accuracy of 88%. This study used professional players for the data collection. Liu et al. [17] employed a SVM with acceleration, gyroscope, and magnetometer data from three sensors to classify various table tennis shots after dimensionality reduction using Principal Component Analysis (PCA). The accuracy achieved is 97%.

Moving beyond shot recognition, strategy recognition in badminton has gained limited attention. Chu et al. [10] integrated computer vision techniques to classify shots and strategies based on player position on the court. Videos used for this research were collected from international tournaments with professional players and have a top-down view. However, this solution only distinguishes six shots and categorizes strategies as offensive or defensive, and relies on vision techniques, which are more expensive to deploy and require calibration. In contrast, our research uses opponent localization data from a mobile UWB setup to perform the classification of 11 different strategy variations with an LSTM model. Furthermore, our approach was designed to incorporate 14 different classified shots to improve the detection of localization-only approaches.

2.2. Ultra-wideband in sports

Table 2: Related works for UWB in sports

Paper	Sport	analysis UWB	analysis Movement	Goal
[2]	ice hockey	✓		accuracy evaluation of UWB systems for ice hockey players
[3]	tennis	✓		accuracy evaluation of UWB systems on tennis court
[19]	tennis	✓		comparison between UWB (10Hz) and GPS (1Hz)
[20]	running/cycling	✓		optimal tag placement
[21]	soccer		✓	comparing load of starting and substitute players
[22]	basketball	✓		accuracy evaluation of UWB systems for basketball players
[23]	badminton		✓	activity profile analysis for different players and games
Our paper	**badminton**		✓	**improved shot recognition and strategy recognition**

For sports analytics, spatial information is of utmost importance to analyze the performance of the athletes. In team sports, the relative movements of the players are evaluated afterward and optimized for the next game. An excellent technology to track athletes is UWB as it is easy to deploy, non-intrusive, and cost-effective while reaching sufficient accuracy. In [20], the authors investigated the placement of the sensors on the athlete and found that placing the tag on the helmet is the best location. Furthermore, the authors conclude that the achieved accuracy of UWB is sufficient to perform a deeper performance analysis. Other sports that were tracked with UWB include soccer [21], basketball [22], and ice hockey [2].

In racket sports, the use of UWB has been tested and validated in [19] and [3]. In both papers, an UWB system is installed on the tennis court and players are tracked. As a result, the movement patterns of the players were clearly visible.

For badminton specific, UWB was used at an international youth tournament in Spain [23]. Twenty-four Spanish junior players on five courts were tracked with a UWB system with six anchors installed at the walls of the sports hall. Based on this data, together with other sensors, including heart rate, an analysis was done on features from the locomotion of the players with PCA. In our research we installed a UWB system at each half of the badminton court, permitting a higher update rate and accuracy of the players' positions and making more detailed analysis possible.

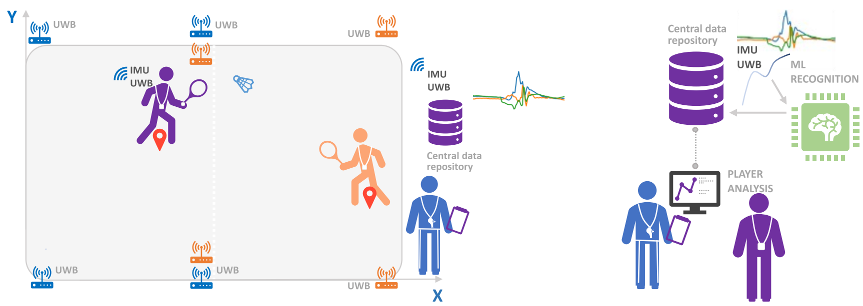
UWB has already been introduced for tracking athletes in sports but from previously discussed works, this paper is the first to accurately track badminton players and simultaneously collect IMU data from the players' rackets. The update rate of the used UWB is 25 Hz permitting a very thorough analysis. Badminton is a fast-paced sport with sudden direction changes and short movements making it challenging to track the location accurately.

Overall, the related work in the field of badminton player analysis covers various aspects such as shot recognition, shot analysis, training, and strategy recognition. Tables 1 shows a summary of the main contributions in this field, along with their most relevant characteristics. While existing approaches have made significant contributions, our research builds upon these foundations by addressing the limitations (dataset realism, number of shots and strategies recognized, and mobile (localization) analysis solutions.) and improving the accuracy and extending badminton player analysis by combining IMU and UWB sensors. UWB has been used in many sports previously, which is summarized in 2. The papers can be divided into two categories: i) papers that analyze the performance of UWB in sports and ii) papers that use the UWB sensor data for analyzing the player's activity and movement.

3. System model and data description

3.1. System model

To alleviate the task of badminton coaches and enhance feedback for badminton players, a system model is proposed, comprising multiple sensors designed to gather data. As shown in Figure 1a, (UWB) anchors are strategically placed around the playing field, while the badminton player is equipped with a UWB mobile device to capture their respective position. Simultaneously, movement data is collected with two IMU sensors attached to the player's racket and wrist. The acquired IMU and UWB data are wirelessly transmitted, utilizing e.g. a Low-Power Wide-Area Network (LPWAN) backbone, and subsequently aggregated in a centralized repository. Here, the data is processed in an offline fashion by the proposed ML models which will classify the played shots and strategies. Succeeding the badminton match, the proposed system allows the coach to offer comprehensive and detailed feedback to the player, as illustrated in Figure 1b.



(a) (b)

Figure 1: The system model overview illustrates (a) a badminton player wearing IMU and UWB sensors, which capture movement and positioning data and communicate with a database, (b) after ML recognition has been applied to the recorded data, the coach analyses the badminton match together with the player and gives feedback based on the played shots and strategies.

3.2. Data description

IMU data was captured using Ax6 Axivity trackers [24], which monitor acceleration and gyroscope readings in three different orientations (x, y, and z). The trackers had a frequency of 100 Hz with an acceleration range of 16 g and a gyroscope range of 2000 dps and were attached to the racket handle and the player's wrist. These locations were chosen because they best measure the movement of the racket and were inspired by the study of [15]. The wrist location is less intrusive than the racket handle, where the balance of the racket is slightly modified by the sensor's low weight but doesn't impede the usability of the racket. In addition, two UWB systems with the TWR technique were used to capture the localization data of both players simultaneously. Both UWB systems had a sample rate of 25 Hz, employed a Kalman filter (KF), and utilized non-interfering UWB channels. The first system operates on channel 2 with a 500 MHz bandwidth and center frequency of 3.9936 GHz, while the second system works at a higher center frequency of 6.4896 GHz. Each system had four anchors placed at the corners of half of the court and a tag, which was carried in a small backpack by the player (see Figure 1a). The TWR technique for UWB stands out as the most resilient localization method when compared to time-difference-of-arrival (TDoA) and angle-of-arrival (AoA). However, it requires determining the distance to each anchor sequentially by exchanging three packets. Consequently, employing additional anchors will reduce the system's update rate which we avoid with measuring at two distinct systems with different frequencies. Both systems can operate without interfering with each other while achieving a maximal update rate for both tags. The UWB hardware used is the Wi-Pos UWB module, which leverages a sub-GHz backbone for scheduling and communication [25]. These advantages make the system battery-powered and easily deployable. The accuracy of the UWB system is visually verified at selected points on the court.

3.2.1. Different shots

To obtain a representative badminton training dataset, we captured thirteen of the most common badminton shots. In addition, these shots are extended with one extra class, that deals with non-shot activities such as walking and other movements registered by players on the badminton court. The following shots were included:

Forehand serve: an underhand serve where the player launches the shuttle far and high over the net.

Backhand serve: a short serve where the player gently hits the shuttle very low over the net.

Forehand clear: a defensive overhand shot where the player launches the shuttle to the other side of the playing field securing a safe position.

Backhand clear: the backhand variant of the clear.

Forehand smash: the strongest and most offensive shot in badminton where the player is standing between the middle and the rear of the court and hits the shuttle to the opponent's field with a steep trajectory, sometimes combined with a jump to gain height.

Forehand drop: an offensive overhand shot in which the shuttles go immediately downward and land as close as possible after the net. The swing is similar to the clear and smash, but the shot is executed with lower acceleration.

Backhand drop: the backhand variant of the drop that is played to neutralize the rally when the opponent puts more pressure on the backhand side of the court. This shot is more technical and requires more training.

Forehand lob: a defensive underhand shot that resembles the forehand serve where the player hits the shuttle far and high over the net with an underhand swing.

Backhand lob: the backhand variant of the lob.

Table 3: Shots measured and classified in this paper. In total, six intermediate and national-level players have participated in the data collection campaign.

	#shots	median duration [s]	offensive /defensive	location	acceleration	swing length
Forehand serve	178	1.01	defensive	front	mid	long
Backhand serve	118	1.02	offensive	front	low	short
Forehand clear	146	0.97	defensive	rear	high	long
Backhand clear	11	0.95	defensive	rear	high	long
Forehand smash	80	1.02	offensive	mid/rear	very high	long
Forehand drop	213	0.98	offensive	rear	mid	long
Backhand drop	38	0.86	neutral	rear	mid	long
Forehand lob	115	0.84	defensive	front	mid	long
Backhand lob	167	0.85	defensive	front	mid	long
Forehand net drop	121	0.69	offensive	front	low	short
Backhand net drop	151	0.70	offensive	front	low	short
Dab	81	0.69	offensive	front	high	short
Drive	259	0.52	offensive	mid	high	short
other	1667	-	-	-	-	

Forehand net drop: a short and gentle shot where the player is positioned close to the net and hits the shuttle softly over the net.

Backhand net drop: the backhand variant of the net drop.

Dab: also known as 'the kill', where the player is close to the net and aims the shuttle to the ground with a very steep trajectory. The racket is a swing with high acceleration and short displacement.

Drive: a flat and quick shot where the player hits the shuttle low over the net with an almost horizontal trajectory.

An overview of all included shots and their expected location is given in Table 3. The backhand variants of the shots have fewer instances and require more technical skills from the player. They are also less often played in professional badminton matches. All data samples that were collected but are not in a specific shot when the player is moving over the court or between rallies are added to the class "other".

3.2.2. Different strategies

One of the main contributions of this paper is the data captured in a real badminton match, which results in a model that could be used in an actual game. In total, the strategies of three different people are collected on two different measurement collections. Strategies are manually labeled based on video recordings. The ground truth labels are generated based on the predetermined strategies executed during the match.

All considered tactics exert pressure on the movement of the enemy player. The opponent is obliged to relocate himself on the court, which limits his options to return the shuttle successfully. In the measurement campaigns included in this research, four different types of strategies were captured, each with their own variations. These strategies are “long diagonals”, “other corners”, “same corners” and “play to the middle”, and are illustrated in Figure 2 together with their variations. The following list provides more details on the positioning and shots played within each strategy.

Long diagonals (LD): In singles play, the longest distance, 8.47 m, is along the diagonal axis of the court. Players can exploit this by making opponents cover the maximum distance, utilizing acceleration effectively. Two variants exist: LD1 involves forcing the opponent from backhand front court to forehand rear court and back, while LD2 entails movement from backhand rear court to forehand front court and back.

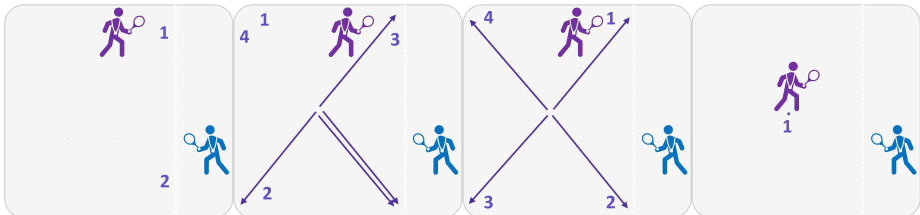
Other corners (OC): To limit an opponent’s acceleration, employ a strategy of changing their running direction by playing consecutively to adjacent corners. Despite covering less distance than the previous tactic, the players cannot run in a straight line because they are returning to the center. Only a partial acceleration component can be reused, posing a greater challenge for opponents, especially those who are fast but less technically skilled. This approach is effective against such competitors. The four variants are: OC1 (backhand front and rear court), OC2 (forehand front and rear court), OC3 (fore- and backhand front court), and OC4 (fore- and backhand rear court).

Same corners (SC): Despite appearing inefficient, the same corner strategy disrupts the opponent’s momentum by preventing the reuse of acceleration components. The opponent must continually return to the central base position after each shot, enhancing the effectiveness of the strategy. It also induces a pattern in the opponent, making shots to different corners more surprising due to the lack of opportunity for full relocation. The four variants are: SC1 (backhand front court), SC2 (forehand front court), SC3 (forehand rear court), and SC4 (backhand rear court).

Play to the middle (PTM): This strategy doesn’t involve player movement but restricts the opponent’s options to playing the shuttle along the line or with high angles. It facilitates coverage of both angles for the executor. Playing from a corner is preferred by the attacker, offering two options: a straight shot or one to the opposite side. The executor covers the straight shot due to its shorter travel time, increasing the likelihood of the opponent playing a crossing shot. Using the middle is a defensive strategy to neutralize options and recover from pressure, but excessive use requires a change in the game plan.

4. Methodology

The proposed methodology for strategy recognition in badminton is two-fold. First, we introduce two distinct CNN models specifically designed to accurately



(a) Long diagonals (LD) (b) Other corners (OC) (c) Same corners (SC) (d) Play to the middle (PTM)

Figure 2: Different variations per strategy, played by the left player, with shots coming from the right player. The strategy 'play to the middle' has only one variation, the three other strategies have variations based on the targeted corner of the court.

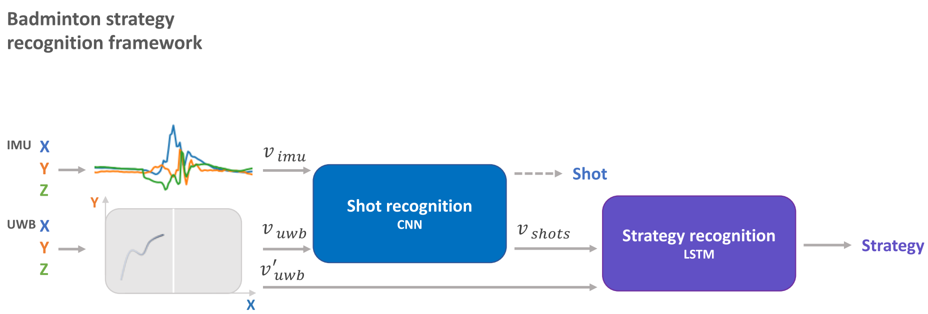


Figure 3: The framework of badminton strategy recognition uses both IMU and UWB data, and the output of an intermediate shot recognition model.

classify badminton shots based on UWB localization, acceleration, and gyroscope data. The first model utilizes 1D convolutional layers, while the second model incorporates 2D convolutional layers. Through a comprehensive comparison, we assess the effectiveness of these two models in shot classification. In the second part, we incorporate a Long-Short-Term Memory (LSTM) model. This LSTM model not only takes into account the shot classification output from the aforementioned CNN models but also considers long-term (3.6 seconds) positional information of the player in order to determine the played strategy by the player.

4.1. Strategy recognition architecture

Figure 3 illustrates the proposed framework used for recognizing the badminton strategy. The initial module comprises a CNN that uses IMU and UWB data. Within a predefined time duration of Δt_{shot} seconds, the CNN performs a single-shot classification. The classifications are accumulated, forming a time series vector v_{shots} that serves as the output of the module. Based on the median duration of the different shots (Table 3), we determined that the optimal time duration parameter is $\Delta t_{shot} = 1$ s, resulting in the following parameter

Table 4: Proposed neural network models for shot and strategy recognition

Shot recognition (1D) (292334 parameters)			**Shot recognition (2D) (853166 parameters)**			**Strategy recognition (514220 parameters)**		
Layer name	**Activation**	**Output size**	**Layer name**	**Activation**	**Output size**	**Layer name**	**Activation**	**Output size**
Input (100,15)		(1500,1)	Input (100,15)		(100,15,1)	Input (90,4)		(90,4)
Notes on input size						**Notes on input size**		
15 = v_{imu} sensor 1 (6: acc xyz + gyro xyz) + sensor 2 (6: acc xyz + gyro xyz) + v_{uwb} (3: xyz))						4 = $v_{uwb}\prime$ (3: xyz) + v_{shots} (1: shot recognition)		
Conv (256x3, s=3)	ReLu	(34,256))	Conv (256x(3x3), s=(1,3))	ReLu	(100,5,256)	LSTM (256)	ReLu	(90,256)
Conv (128x3, s=3)	ReLu	(11,128)	Conv (128x(3x3), s=(1,3))	ReLu	(100,2,128)	Dropout (35%)		(90,256)
Dropout (30%)		(11,128)	Dropout (35%)		(100,2,128)	LSTM (128)	TanH	(90x128)
Conv (128x3, s=1)	ReLu	(11,128)	Conv (128x(5x3), s=(1,3))	ReLu	(100,1,128)	LSTM (64)	TanH	(64)
Conv (64x3, s=1)	ReLu	(9, 64)	Conv (64x(5x3), s=(1,3))	ReLu	(100,1,64)	Dropout (35%)		(64)
Dropout (30%)		(9,64)	Dropout (35%)		(100,1,64)	Dense (32)	ReLu	32
Conv (64x8, s=1)	ReLu	(9,64)	Conv (64x(7x3), s=(1,1))	ReLu	(100,1,64)	Output (12)	Softmax	12
Conv (32x8, s=1)	ReLu	(2,32)	Conv (32x(7x3), s=(1,1))	ReLu	(100,1,32)			
Dropout (30%)		(2,32)	Dropout (35%)		(100,1,32)			
Flatten	ReLu	(64)	Flatten	ReLu	(3200)			
Batchnormalization		(64)	Batchnormalization		(3200)			
Dense (256)	ReLu	(256)	Output (14)	Softmax	(14)			
Dropout (30%)		(256)						
Dense (128)	ReLu	(128)						
Dropout (30%)		(128)						
Dense (64)	ReLu	(64)						
Output (14)	Softmax	(14)						

values for shot recognition: $v_{imu} = 12 \times 100$ ($x \times y \times z$ for 2 IMU sensors) and $v_{uwb} = 2 \times 25$ ($x \times y$ for 1 UWB sensor). Before data is added to the strategy recognition model, it is augmented by translating and rotating it on the court to better generalize to other players and noise in the localization system.

The strategy recognition model accumulates samples for $\Delta t_{strategy} = 3.6$s, which is experimentally determined, based on the time in which the longest strategy is typically completed. As such, $v_{shots} = 2 \times 90$ are accumulated (for each player), resampled at 25 Hz to align with the UWB localization data, which in addition is passed to the strategy recognition model with an input vector ($v'_{uwb} = 2 \times 2 \times 90$). Notably, the length of the LSTM model differs from that of the shot recognition model (v_{uwb}). Finally, the strategy recognition module provides the strategy classifications for each $\Delta t_{strategy} = 3.6$ s. In the following subsection, we provide more details on the CNN and LSTM models architecture, for shot and strategy recognition, respectively.

4.2. Shot recognition CNN models

1D CNN model: in light of the research conducted by Ghosh et al. [15], we propose a 1D convolutional model for badminton shot recognition. The input shape of the model is shown in Table 4, which shows the arrangement of the IMU and UWB data, corresponding to Figure 3. Specifically, the acceleration data from the arm sensor is followed by the gyroscope data from the same sensor, with similar data incorporation for the racket. This sequential data arrangement forms a continuous series. The architecture of the 1D model, as illustrated in Table 4, comprises three pairs of 1D convolutional layers with various stride lengths (s). Each pair is followed by a dropout layer (with a dropout rate of 30%), to improve generalization. Subsequently, a flatten layer, a batch normalization layer, and four dense layers follow. The first three dense layers are interspersed with dropout layers (with a dropout rate of 30%). A Rectified Linear Unit (ReLU) activation function is utilized for all layers except the final dense layer, which adopts the softmax function for classification.

2D CNN model: the decision to include 2D convolutional layers in the second model stems from the research carried out by Steels et al. [11]. Their study proposed a straightforward CNN architecture that uses 2D convolutional layers. In contrast to their IMU-based approach, we add localization information as input to the model. The input shape of this model is represented in Table 4, where the first dimension corresponds to a time series, and the second to the data type. The ordering of the IMU and UWB data is aligned with that of the 1D model. Notably, this input configuration parallels the shape of an image, as CNNs are commonly employed for image recognition tasks. Specifically, this input image has a width of 12 (sensor axis) and a height of 100 (temporal resolution). The architecture of the 2D model, as illustrated in Table 4, comprises three pairs of convolutional layers. In contrast to the 1D model, the 2D model employs 2D convolutional layers and with 2D stride lengths (s). In the 2D model, the dropout layers are configured with a dropout rate of 35%. One notable advantage of this model over the 1D model is the spatio-temporal awareness within the kernels, which helps to consider values from each sensor input across a brief temporal duration.

4.3. Strategy recognition LSTM models

The strategy recognition model based on the LSTM architecture can recognize the strategy played by a badminton player. This model uses both shot information and localization data for the prediction of the strategy. The architecture of the LSTM model is depicted in Table 4. The model comprises multiple stacked LSTM layers, to enable the model to reach a high level of abstraction. The first layer is an input layer, with shape $(90, 4)$, which corresponds to the frame size (90) and the number of dimensions (4). This layer is followed by a first LSTM layer with 256 memory cells with a L2 regularizer for both kernel and recurrent regularization. This layer passes the entire sequence to the next LSTM layer, which is placed behind a dropout layer with a rate of 35%. The second and third LSTM layers have, respectively, 128 and 64 units, and both have the same regularizers as the first LSTM layer. Finally a dropout layer with rate 35% and two dense layers of, respectively, 32 neurons and one neuron per class.

The inclusion of shot data in the model offers valuable insights into the player's positional dynamics on the badminton court, as certain shots are specifically executed within designated areas. For example, a clear shot is typically played from the rear court targeting the rear court of the opponent. A net drop is always played close to the net. The locations where the shots are mostly played are given in Table 3. By incorporating shot information, the model gains additional contextual cues, which have the potential to enhance accuracy and precision in strategy recognition. In addition, the integration of shot data may introduce the capability to detect "non-strategy" frames that closely resemble genuine strategy frames, characterized by limited or absent shot information. As such, we can effectively differentiate between "non-strategy" accidental walking lines and actual strategy frames. It is noteworthy that these distinctions, although not evident in conventional performance metrics, hold practical significance for real-world applications.

4.4. Evaluation methodology

To evaluate the proposed methodology, we perform model training using a dataset randomly divided into train, validation, and test sets, with proportions of 64%, 20% and 16%, respectively. In order to address class imbalance, we applied weights to compensate for classes with fewer samples. The weight calculation followed the formula: $w_i = \frac{1}{n_i} \cdot \frac{n}{2}$, where w_i represents the weight for class i, n_i denotes the number of samples in that class and n represents the total number of data frames. The model was trained for 200 epochs with a fixed initial learning rate of 0.001. Starting from epoch 100, the learning rate was updated at each epoch using the formula: $lr_{\text{new}} = lr_{\text{current}} \cdot e^{-0.02}$. This ensured a gradual reduction in the learning rate, allowing the model to fine-tune its performance over time. To enable lightweight deployment and evaluation on edge and embedded devices in future work [26], the models were deliberately restricted to fewer than one million parameters, ensuring efficiency and adaptability in resource-limited environments. More specifically, the 1D CNN model, 2D CNN model and LSTM model have 292334, 853166 and 514220 parameters, respectively. Although we do not focus on embedded and edge inference in this paper, as shown in [26], it becomes feasible to run such models on the edge (where a wireless technology such as Wi-Fi, BLE or ZigBee can be used to transmit raw IMU and UWB data. Moreover, with optimizations such as pre-training pruning and model quantization, it becomes possible to run such models directly on the device (mitigating raw data transmission), with a typical reduction of only a few percent in accuracy.

5. Results

In this section, we will present localization insights into the UWB localization system for badminton player tracking. Due to the fast pace of the sport, sudden direction changes, and the blocking effects of the player's torso towards some of the anchors, we don't expect the cm-level accuracy UWB can achieve but we will show that it is sufficient to derive conclusions from. After the localization system, we will discuss shot recognition with the proposed machine learning models. Finally, the results of the strategy recognition are presented.

5.1. Localization

The use of UWB for the tracking of badminton players adds absolute spatial information to the system. The commercial-off-the-shelf (COTS) UWB localization system is used to validate the location where the shots were played during data collection. For every shot collected for **shot recognition**, we noted the location and assigned them to a zone on the court. The court of the player is divided into 5 zones: backhand front court (BH FC), backhand rear court (BH RC), forehand front court (FH FC), forehand rear court (FH RC), and mid

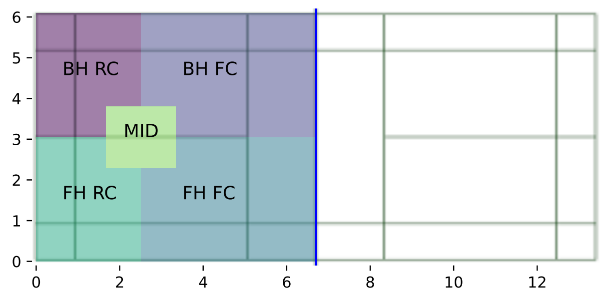


Figure 4: For the analysis of the UWB localization system, the court is divided in 5 different zones: the middle zone (MID) and 4 corners depending on the side (back- and forehand) and the distance from the net (front and rear court).

court (MC). As the player wears the UWB tag on his back, the zone's front court zones are slightly larger than the rear court to have a smooth transition. These zones are shown in Figure 4. In Table 5, for all shots, the percentage of shots that the player was in the zone is shown. For overhand shots (clear, drop, smash), the majority (68 - 82% of the shots) of the shots are detected in the rear court. Less than 10% of these shots are detected in the front court. On the other hand, net shots are assigned to the front court in 92%, 95%, and 99% of the cases for the backhand net drop, forehand net drop, and dab, respectively. The zone where the lob, serve, and drive are played is mostly the front court and the middle. From this realistic experiment, a dataset was collected with UWB locations for the player and thirteen different shots. We showed that the localization of the shots is sufficient to place most of the shots in the expected zone. However, the division into zones is better for the x-axis (front and rear court) than for the y-axis (forehand and backhand side of the court). This is explained both by the data and properties of the system. If the player is not completely returning to the center of the court after hitting the shuttle, he might play a forehand shot on the backhand side and vice versa. The UWB anchors are closer together in the y-direction, decreasing the dilution of precision of the UWB localization and therefore the accuracy in this dimension. The last remark is about the difference in the technical execution of the different players and their physical condition. A taller player will have a longer arm reach and not move as deep in the corner as a shorter player.

For the **strategy recognition** data, the same zones are used to evaluate the execution and detection of the strategies. In Table 6, the total time per strategy and the time in each of the five zones are given. For the long diagonal variants, the majority of the time the opponent is in the middle of the court travelling between 2 opposite corners. For LD1, these are the backhand front court and the forehand rear court where the opponent is 28 and 27 percent of the time, respectively. Similar to the other long diagonal variant, with 32 and 23 percent of the time in the backhand rear court and forehand front court zone. During

Table 5: The time that the executor is a specific zone for the shot recognition. In most cases, the shots are played in the expected

Zone	BH FC	BH RC	FH FC	FH RC	MID	Front court	Rear court
Forehand serve	19%	9%	**29**%	9%	**33**%	**49**%	19%
Backhand serve	**26**%	1%	**35**%	7%	**31**%	**61**%	9%
Forehand clear	4%	**41**%	6%	**32**%	18%	10%	**72**%
Backhand clear	0%	**35**%	0%	**35**%	**29**%	0%	**71**%
Forehand smash	3%	**29**%	6%	**39**%	**23**%	9%	**68**%
Forehand drop	2%	**34**%	2%	**46**%	17%	4%	**80**%
Backhand drop	2%	**35**%	3%	**47**%	14%	5%	**82**%
Forehand lob	**25**%	5%	**40**%	10%	20%	**65**%	15%
Backhand lob	**37**%	12%	**22**%	9%	**20**%	**58**%	**21**%
Forehand net drop	**34**%	1%	**61**%	0%	4%	**95**%	2%
Backhand net drop	**50**%	0%	**42**%	2%	6%	**92**%	3%
Dab	**39**%	0%	**59**%	0%	1%	**99**%	0%
Drive	**22**%	**20**%	**32**%	8%	17%	**54**%	**29**%

the PTM strategy, the opponent divides its time over both front court zones and the middle zone equally. In the PTM strategy, the player spends the majority of the time in one of the front court zones. This similarity with the OC3 strategy, which involves switching between the two front court zones, is noteworthy.. The other corners (OC) strategy forces the opponent to move between 2 corners on the same side of the court. For all four variants of this strategy, the opponent is mainly in two zones. For the second variant, where the opponent moves in the forehand side of the court, 24% of the time the player is detected in the middle zone of the court which shows that the players return best to the central position in this variant. The player is only detected 2% on the opposing side for all four variants. The final strategy, same corners (SC), is where the opponent is deceived after returning to the central position on the field by playing in the same corner and suddenly switches to the opposite direction. The strategy involving the backhand side of the court has more than 60% of the time in the same zone. For the other variants about half of the time, the player is in the targeted zone. For this strategy, the player is more often in zones that were not targeted by the strategy, showing that the opponent was deceived successfully.

The localization information analysis corresponds to the expected values. Therefore, UWB is a valid candidate to add spatial information to badminton shots and strategy recognition and enables automatic individualized feedback. The use of an extended Kalman filter smooths the player's movement without removing essential information about corner displacements.

5.2. Recognizing individual badminton shots using CNNs

In this part, we examine how well 1D and 2D CNN models recognize badminton shots. We evaluate both 1D and 2D CNN with only IMU sensors, similar to existing related work, and compare this to the results with UWB data included. These models with only IMU sensors are used as a baseline for our novel dataset. Our goal is to show how different sensor types influence shot recognition systems for real-world badminton use. The results presented here take the class imbalance into account by adjusting the weights of the different classes during training.

Table 6: The time that the executor is a specific zone for each of the strategies. For the long diagonal strategy, players must cross the middle court. LD and OC have 2 frequently used corners based on the variant. SC has one frequently used corner

	Time [s]	BH FC	BH RC	FH FC	FH RC	MC
LD1	265	**28**%	3%	2%	**27**%	**40**%
LD2	278	2%	**32**%	**23**%	1%	**42**%
PTM	426	**36**%	5%	**29**%	1%	**29**%
OC1	401	**47**%	**44**%	1%	1%	8%
OC2	383	2%	0%	**38**%	**35**%	**24**%
OC3	168	**53**%	1%	**36**%	2%	8%
OC4	170	2%	**48**%	0%	**41**%	8%
SC1	296	**66**%	7%	7%	5%	15%
SC2	434	15%	14%	**48**%	4%	20%
SC3	137	6%	15%	6%	**49**%	**23**%
SC4	112	11%	**61**%	2%	9%	17%

1D CNN IMU: Table 7 illustrates the results obtained for recognizing individual badminton shots using the proposed 1D and 2D CNNs. The 1D model that used only IMU data achieved a test accuracy of 85.33%, with a precision of 0.8545, recall of 0.8533, and an f1-score of 0.8513. These are positive results, considering the model's task of distinguishing among fourteen different classes. Examining this confusion matrix, we observe that the model occasionally confuses between the forehand clear shots and the smash shots. Given their similarity and the variations in players' abilities, such confusion can be expected. Similar observations can be made for drive and dab shots. The 'other' class poses the greatest challenge in terms of classification. Due to the diverse nature and high variability (various types of movement) within this class, its performance is lacking compared to the other classes, leading to lower accuracy. When we exclude this class from the evaluation, the test accuracy results in 88.42%.

1D CNN IMU + UWB: with the addition of the UWB location data, a slight accuracy drop (85.19%) can be observed. This slight accuracy variation can be caused by several reasons: (i) the models are very similar and may be influenced by random choices while training the CNN model, (ii) we argue that due to the different types of data in 1D times series, machine learning and making prediction becomes more complex, as there are two different sources of information (IMU and UWB) along the same input dimension, sharing the same convolutional kernels. Leaving out the other class results in an accuracy of 86.80%, which is only a slight increase of 1.61% and still lower than the 1D results only from the IMU.

2D CNN IMU: compared to the 1D CNN, the 2D CNN achieves a higher accuracy of 88.99% (+3.66%), with precision, recall, and f1-score values of 0.8908, 0.8899, and 0.8895, respectively. Although there are fewer misclassified smashes and forehand clears, some confusion remains. Furthermore, the 'other' class still exhibits poor performance. By excluding this class from the accuracy calculation, the 2D model achieves an accuracy of 91.35%.

2D CNN IMU + UWB: adding UWB localization data to the 2D model results in an accuracy of 90.90%. This time, the addition of the location data solves the smash and forehand clear confusion problem as well as the confusion between the dab and the drive. However, the accuracy of the 'other' class has dropped. Adding the UWB localization data results in an even higher data variety within the 'other' class, where the position of the players changes significantly in between shots. When we leave the 'other' class out of the calculation of the accuracy, this model reaches a result of 94.43%, which is a very promising result. The confusion matrix for this 2D CNN model is given in Figure 5a.

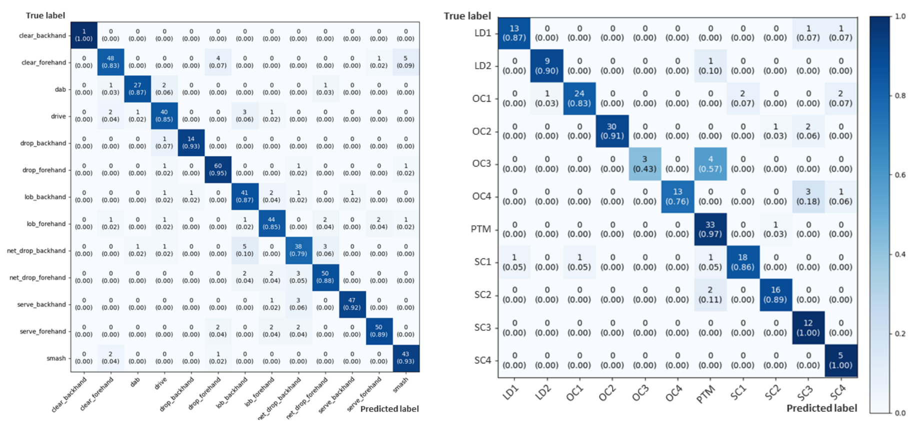
5.3. Recognizing badminton strategies using LSTMs

UWB-only: when only the opponent's position is passed to the model, the main challenge lies in differentiating strategy classes from non-strategy classes. A considerable number of strategies are classified as non-strategies, resulting in an overall accuracy of 53.5% for this model. These misclassifications occur due to the player randomly walking on the field during the data collection, labeled as non-strategy. These movement patterns overlap with certain strategies, although no actual shots have been placed. In addition, a number of misclassified strategy variations are mainly the result of logical errors. For example, strategy OC1 partially overlaps with both SC1 and SC4. Similarly, OC4 overlaps with SC3 and SC4. Additionally, there are numerous instances predicted as PTM, which is reasonable considering that the middle position serves as the base for every strategy, resulting in certain similarities with the PTM strategy. Since most mistakes occur in classifying the rest class instances, it is valuable to investigate the performance when excluding this class. In such cases, the model only needs to differentiate between the variations of different strategies. The model trained on all classes except the rest class achieves a higher accuracy of 79.5%, representing a significant improvement of 26% compared to the model that includes the rest class. Notably, the misclassifications between the different strategy variations persist, reaffirming the presence of persistent logical faults as previously mentioned.

UWB and shots: with this extra shot data of both players, the model is able to reach an accuracy of nearly 84% and a accuracy of 80%. These results are similar to the predictions of the model which only received the localization data as an input. Leaving out the rest class, like in the previous section, also improved the classification. The confusion matrix is enclosed in Figure 5b and The model with UWB and shots scores an accuracy of 88% with a precision and recall of 0.87 and 0.86. The phenomenon of logical confusion between strategy variations is less present in this model.The PTM strategy is still predicted more often than any other strategy variation and some confusion is occurring with the OC3 tactic. This could be the result of the strategy that has not been played close enough to the net, as a result of which it is confused with PTM.

Table 7: Accuracy for shot and strategy recognition. Adding localization in strategy recognition improves the performance.

Model	Accuracy (all classes)	Accuracy (w/o other class)
Shot recognition		
1D IMU	85.33%	88.42%
1D IMU + UWB	85.19%	86.80%
2D IMU	88.99%	91.35%
2D IMU + UWB	90.90%	94.43%
Strategy recognition		
UWB-only	53.5%	79.5%
UWB and shots	80%	86.0%



(a) Shot classification 2D CNN IMU + UWB (b) Strategy classification LSTM UWB + shots

Figure 5: Confusion matrices of the shot and strategy classification models show that the model accurately predicts the majority of the classes and is only confused between similar shots and strategies.

6. Conclusions and Future Work

Analyzing and improving the performance of badminton players requires extensive effort and coordination between the player and the coach. In this paper, we have proposed a machine learning-based methodology for automating the analysis of shots and strategies played by badminton players during a match. Our methodology is based on the use of non-intrusive UWB and IMU sensors to collect movement and positioning data, which is then used to train shot and strategy recognition neural networks. The UWB sensors enable information on the location of the player. Most of the shots and strategies recorded in the dataset consistently fell within the anticipated zone, indicating the potential to utilize the UWB localization system to enhance badminton training. Additionally, we compared 1D and 2D CNN architectures for shot recognition using IMU data or IMU and UWB data. The 2D model with both IMU and UWB data achieved the highest accuracy (90.90%) for all 13 types of shots and the other class. The strategy recognition model makes use of an LSTM model, with the aim of identifying longer-term patterns in the data, and achieves SOTA accuracy (86%) using both UWB and predicted shots.

In future work, other researchers can test and compare new methodologies on the open source datasets provided in this paper. Additionally, to achieve a real-time feedback system, the complexity trade-offs of a real-time neural network-based classification system can be investigated together with a personalized and self-training model to increase accuracy for individual players even further.

Acknowledgment

The authors would like to thank all the players who participated in the data collection.

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