RESEARCH ARTICLE

Deep Learning

Skeletal point analysis to determine the accuracy of forehand smash shots played by badminton players [†]

N Krishnaram, J Ahamed, N Sathyamoorthy, KD Sandaruwan and AMKB Athapaththu
University of Colombo School of Computing, UCSC Building Complex, 35 Reid Ave, Colombo 00700, Sri Lanka.

Abstract: This study aims to address the scarcity of scientific research on badminton performance analysis, specifically the accuracy of forehand smash shots. The authors propose the use of a skeletal coordinates-based technology to analyze a badminton player's biomechanics. To achieve this, specific techniques, such as formulating a quantitative description of badminton smash biomechanics based on the available literature, collecting video footage of badminton rallies and processing them using a MediaPipe-powered Python program, were followed. Three main approaches were considered for the analysis, defining a dynamic mathematical model, creating a player-to-player comparison model, and developing a machine-learning model. Preliminary results suggest that the use of three-dimensional points in comparison to two-dimensional points provides more accuracy in detecting the angle between three skeletal points from any camera perspective. This research also proposes a novel approach to compare two players and evaluate their skills based on a set of key parameters. The study explores the integration of machine learning algorithms to classify and predict player performance accurately. All three proposed methods enable coaches and players to identify and improve upon their weaknesses, enhancing their overall performance, as these findings have the potential to reduce subjectivity in measuring shot accuracy during training and to provide players with a more objective means of evaluating their performance. The proposed methodology and results contribute to a better understanding of badminton biomechanics and have implications for future research in this field.

Keywords: Badminton forehand smash, biomechanics, machine learning, mathematical model, mediapipe, shot analysis.

INTRODUCTION

Badminton is a popular racquet sport (He & Gong, 2022) in which players experience multiple intense actions and specific movement patterns, including numerous explosive shifts over short distances (Rusdiana, 2021). In badminton, actions such as 'smash' and 'drop' must be mastered as they can heavily influence in changing the pace of the game in favour of the player (He & Gong, 2022). Out of various smash action styles in badminton, this study is about 'forehand smash' as it is an overhead shot performed at full power by attacking the opponent in a dive movement, thus making it one of the game-changer actions.

According to the literature, a successful smash shot can be divided into four distinct phases (Rusdiana, 2021) as shown in Figure 1: preparation, acceleration, contact point and follow-through.

Recognizing body posture and motion is a key physical function for maintaining body balance (Zeng & Zhao, 2011). The integration of sports science into coaching has been pivotal in the significant advancements in international sports performance over the past two decades, particularly in analyzing players' biomechanics to identify and rectify shot-related mistakes (Vora, 2018). Several studies have been conducted to investigate the

biomechanics of badminton, using various sensors, cameras, reflective markers, and motion analysis software

to analyze different shots and techniques (Salim *et al.*, 2010; Hsueh *et al.*. 2012; Rusdiana *et al.*, 2020).
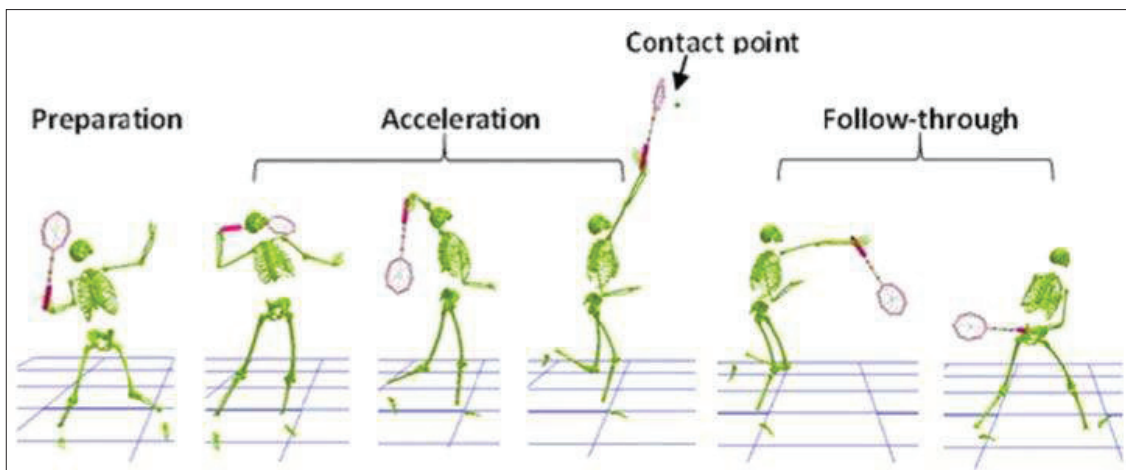

Figure 1: Phases of badminton forehand smash (Zhang *et al.*, 2016)

Analyzing a player's playing style, performance indicators, and so on has been observed in many popular sports, including badminton. However, the majority of such performance analysis methods such as skeletal point based technologies, require a player to be surrounded by multiple pieces of equipment, or to wear external peripherals that can help track their performance based on their body movements, heart rate, and so on. Although these technologies have been shown to be effective (Ananth *et al.*, 2019), it is challenging for a player to perform at their peak while wearing these peripherals.

However, there is relatively less research on pose recognition and video analysis (He & Gong, 2022). In comparison to other racquet sports, badminton has received very little scientific research attention (Tan *et al.*, 2016). There is a demand for a plug and play technology that can help track the performance of a badminton player without relying on any external peripherals, especially when playing a sport like badminton, where a player's weight and accessories such as the racquet and shuttlecock are very important in affecting their optimal gameplay. Furthermore, based on the market conditions at the time of this research, these external peripherals could cost the players a fortune.

The aims of this research are twofold: to reduce subjectivity in measuring the accuracy of badminton shots during training sessions and to empower players to evaluate their shots independently. This will be

achieved by developing a simplified dynamic model that can effectively identify instances where a shot is played inaccurately.

Related work

The smash shot is a crucial technique in badminton, particularly the forehand smash. Mastering this shot is essential for players to gain points effectively (Kurnia *et al.*, 2020; Rusdiana *et al.*, 2021). Putra & Lumintuarso (2020) have investigated the biomechanical principle of the forehand badminton smash. Biomechanical studies have shown its significance and effectiveness in producing a fast shuttlecock rate (Vora, 2018).

In any sport, the main target of the players and coaches is to achieve the maximum level of success, and the aid of science and technology can be used to achieve it. What they expect is a way to evaluate the skill movements and the ability to correct themselves (Bartlett, 2021). It is discovered that this kind of biomechanical analysis is useful to improve the efficacy of approaches as well as the development of new and sustainable motions in technological development (Lu & Chang, 2012).

A recent study conducted by Ghazali *et al.* (2022) focused on stroke classification in badminton, employing an inertial sensor and a machine learning approach, whereas Kurnia *et al.* (2020) explored the movement patterns of the drop shot and smash in badminton using

motion sensors such as accelerometers and gyroscopes. Inertial Measurement Unit (IMU) sensors have also been used in several research projects (Ananth *et al*. 2019). Moreover, reflective markers were employed in several studies (Salim *et al*. 2010; Hsueh *et al*., 2012; Rusdiana, *et al*. 2020) to capture the biomechanical points of badminton players. These markers enable precise tracking and analysis of specific body movements and joint angles during gameplay. According to a review (Adesida *et al.*, 2019), there is growing interest in using wearable technology to quantify kinetic and kinematic characteristics in sports, to better understand movement and discern skill levels.

However, Alderson (2015) claims that the developed marker-less system is capable of estimating accurate joint kinematics in a variety of blind body pose estimation scenarios (*i.e.*, sporting activities) and provides an exciting and promising foundation for the non-invasive on-field measurement of athletes during match play. Using deep learning models (GoogleNet, Vgg-16 and RestNet 18) Ying *et al*. (2022) have performed research to recognise badminton smashing through video performance, where they were able to achieve the best accuracy of 97.51% and 98.86% on training and testing data sets, respectively, on ResNet-18. Tsai *et al*. (1998) used Direct Linear Transformation (DLT) to calculate the 19 3D coordinates for the segment endpoints and racquet from the recorded video. Many studies (Chu & Situmeang, 2017; Rahmad *et al*., 2020; Ying *et al*., 2022) have used video footage from the Badminton World TV YouTube channel with a camera angle which focuses in a top-down manner. Also, video-based analysis has been used not only to detect players, but also to detect the court (Chu & Situmeang, 2017), identify badminton shot events using shuttlecock trajectory data from recorded videos (Ju *et al*., 2020) and provide game statistics.

If we consider other racquet sports such as Tennis, Squash, Table Tennis, and Racquetball, studies have been done to identify shots using IMU sensors (Torres-Luque *et al*., 2011; Sharma *et al*., 2018; Williams *et al*., 2021), compare tennis serves between professional and elite players using MediaPipe (Liu & Sun, 2022), analyse backhand strokes of 3 different levels of players (Ghani *et al.*, 2019), determine the number of shots in a rally through recorded video footage (Torres-Luque *et al*. 2011), etc.

Human pose estimation (HPE) is a popular research topic in computer vision, with applications in video surveillance, medical assistance, and sports motion analysis. Numerous HPE libraries have been developed to detect and extract motion from real-world, and the usage of depth cameras and pose estimation models have shown high reliability for such marker-less motion-capturing applications. There are various skeleton-based HPE libraries available, each with its own set of advantages and disadvantages (Chung *et al.*, 2022).

MATERIALS AND METHODS

Figure 2 shows a top-down block diagram that provides a high-level overview of the research methodology employed in this study.

The research team conducted interviews with domain experts and external advisors to investigate the biomechanics of a badminton player while playing a forehand smash shot. It was revealed that coaches often assess angles between body parts such as elbow, shoulder joint, wrist and so on, yet a quantified description of these biomechanics was lacking in existing badminton resources. Thus, the research team bridged this gap by translating theoretical knowledge into mathematical conditions, taking the distances between joints of the body into account, and calculate the angles between them. Choosing suitable technology for detecting skeletal points on a player's body is crucial for obtaining accurate and reliable data for analysis, considering factors such as the nature of detected skeletal points (2D or 3D coordinates), its performance with minimal hardware specifications, and so on.

The study introduces the simple dynamic model, which involves evaluating calculated angles against predefined conditions. If these conditions are met, the shot is deemed to meet the required standards, offering a precise quantitative approach to assessing forehand smash shot biomechanics. Additionally, the angles obtained from one player's analysis can be compared with those of another, enabling a player-to-player comparison model for self-evaluation and technique improvement. This player-to-player comparison model can be used by coaches and players alike as a tool to improve their technique by referencing the ideal biomechanics of a badminton smash shot. Alternatively, the extracted skeletal points can serve as a dataset for machine learning algorithms, which can predict shot accuracy without relying on mathematical formulas.

However, to develop these models, it is crucial to select a suitable technology to extract 3D skeletal points from a data set comprising forehand smash shots played

by professional players. The selection of an appropriate perspective to record the shots, a suitable aspect ratio, preprocessing techniques such as cutting the videos into separate shots, and normalization of the shots are some of the data collection and preprocessing methodologies

that should be followed. Furthermore, the generated results from all three approaches will be evaluated with expert opinion to determine their accuracy and feasibility in analyzing a badminton forehand smash shot.
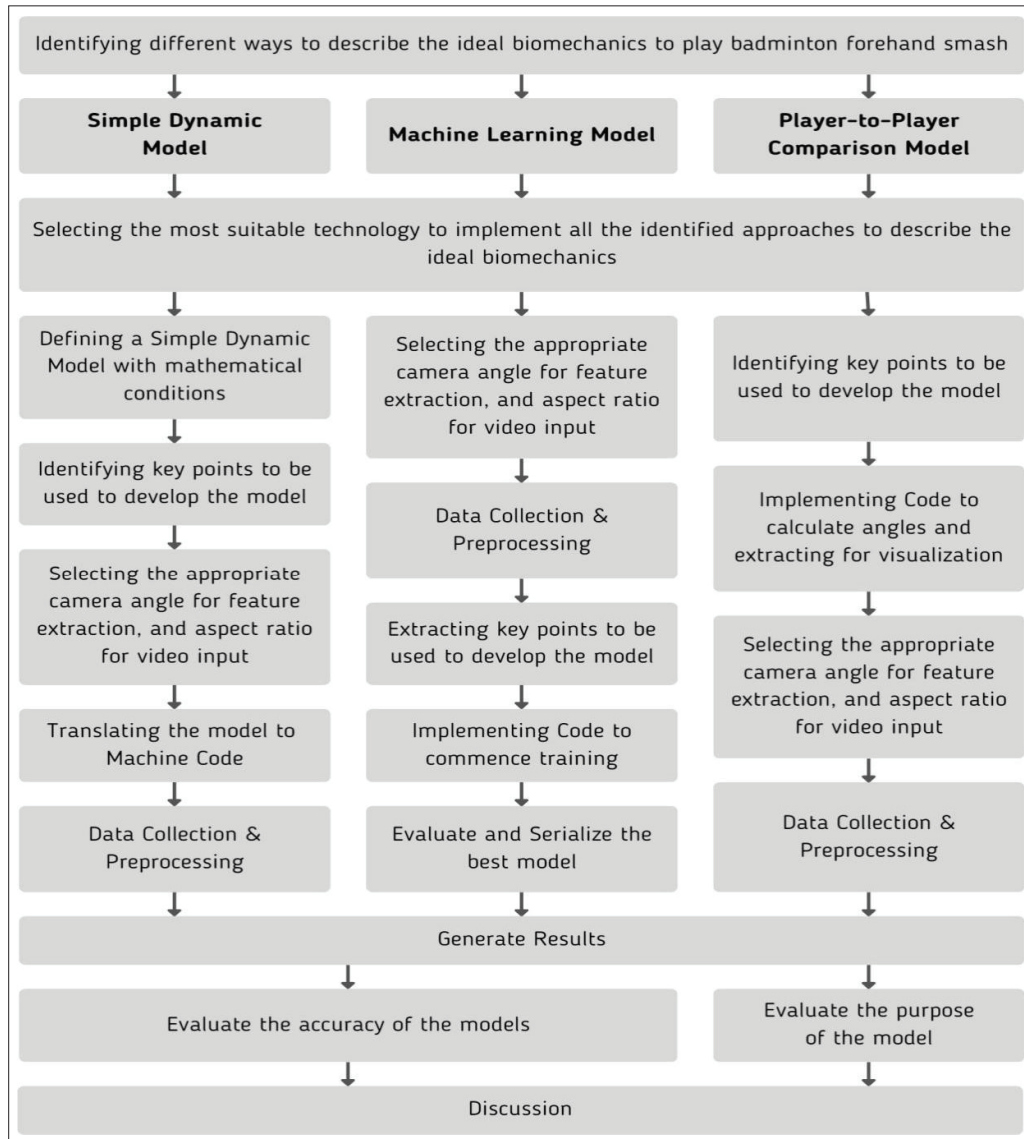

Figure 2: High-level overview of the research methodology

Implementation

Authors have proposed three approaches to describe the ideal biomechanics of a badminton smash shot: defining

a simple dynamic model, developing a player-to-player comparison model, and building a machine-learning model.

Selecting the suitable technology

This study reviewed the official documentation of some of the Human pose detection libraries, and Table 1 depicts the overall comparison among the popular technologies. Among the 4 most popular computer vision technologies used for human pose estimation, BlazePose excels in multiple areas, including optimized performance for both single and multiple-person detection, low flickering, CPU-edged device compatibility, and high processing speed, thus making it the suitable technology for human pose estimation for this study. MediaPipe is a technology that is built using BlazePose. Throughout the research MediaPipe was used to extract the skeletal points.

Definition and development of a simple dynamic model

To achieve a simple dynamic model in which body movements are mathematically described, the authors translated theoretical knowledge from available literature and YouTube explanatory videos into a set of mathematical conditions, and these conditions were converted into a MediaPipe-powered Python Program.

Table 1: Technology Comparison Matrix

Technology	Single/Multiple	2D/3D	Approach	CPU/GPU	Flicker/Jitter	Key points	Speed	Optimized
BlazePose (Bazarevsky *et al.*, 2020)	Single	2D 3D	Bottom-up	CPU	Low	33	High	Yes
OpenPose 2D (Cao *et al.*, 2018)	Multiple	2D	Bottom-up	GPU	Low	135	Low	No
OpenPose 3D (Nakano *et al.*, 2020)	Single	3D	Bottom-up	GPU	Low	135	Low	No
AlphaPose 3D (Fang *et al.*, 2022)	Multiple	2D 3D	Top-down	GPU	High	26	Low	No
YOLOv7 3D (Wang *et al*, 2022)	Multiple	2D 3D	Top-down Bottom-up	GPU	High	17	Low	No

Defining a simple dynamic model

To identify a forward smash attempt as successful throughout the four stages of the shot, the following set of conditions must be satisfied (note: all angles are presented in degrees):
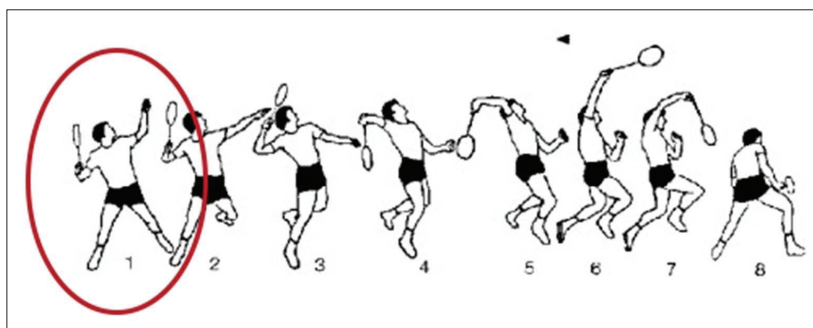
Preparation phase

Figure 3: Smash phase - Preparation phase (Available at: https://jordynhealy.wordpress.com/ biomechanical-analysis/)

Angle in between the dominant elbow -
(let wrist = W, elbow = E, shoulder = S)

   = Angle $WES \leq 75°$ and

   = Angle WES $\geq 30°$

Angle in between dominant underarm -
(let elbow = E, shoulder = S, hip = H)

   = Angle $ESH > 90°$ and

   = Angle $ESH \geq 45°$

Angle in between non-dominant underarm -
(let elbow = E', shoulder = S', hip = H')

   = Angle E'S'H' $> 90°$

Dominant legs should be behind the body. The non-dominant leg should be in front. -
(let ankle = A, hip = H, non dominant hip = H')

   = Angle AHH' $> 90°$

Angle between dominant arm and chest -
(let elbow = E, shoulder = S, non-dominant shoulder = S')

   = Angle ESS' $> 135°$ (State 01)

Record the angle in between the dominant wrist -
(let elbow = E, wrist = W, index = I)

   = Angle EWI   (State 01)

Acceleration phase

Hip should move forward, giving a force
Elbow should come forward, following the hip -
(let elbow = E, shoulder = S, non-dominant shoulder = S')

   = Angle ESS' $< 135°$ (*State* 02)

Difference between State 01 and State 02

   = |State 01 - State 02| $\geq 30°$ and

   = |State 01 − State 02| $\leq 60°$

The racquet should go behind, *i.e.*, Wrist angle should change
Record the angle in between the dominant wrist -
(let elbow = E, wrist = W, index = I)

   = Angle EWI (State 02)

Difference between State 01 and State 02 of Angle EWI

   = |State 01 - State 02| $\geq 15°$

Figure 4:   Smash phase - Acceleration phase (Available at: https://jordynhealy.wordpress.com/biomechanical-analysis/)

Figure 5:   Smash phase - Contact point (Available at: https://jordynhealy.wordpress.com/biomechanical-analysis/)

Contact point

Angle between the dominant elbow -
(let wrist = W, elbow = E, shoulder = S)
    = Angle WES > 135°
The racquet should come forward. *i.e.*, Wrist angle should change. Record the angle in between the dominant wrist
(let elbow = E, wrist = W, index = I)
    = Angle EWI (State 03)
Difference between State 01 and State 02 of Angle EWI
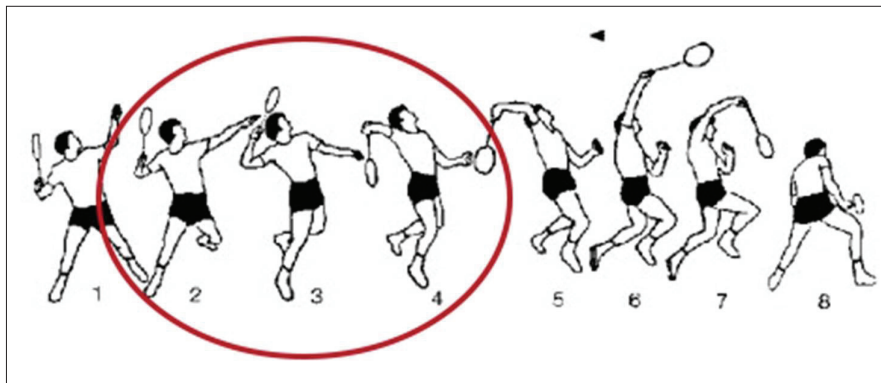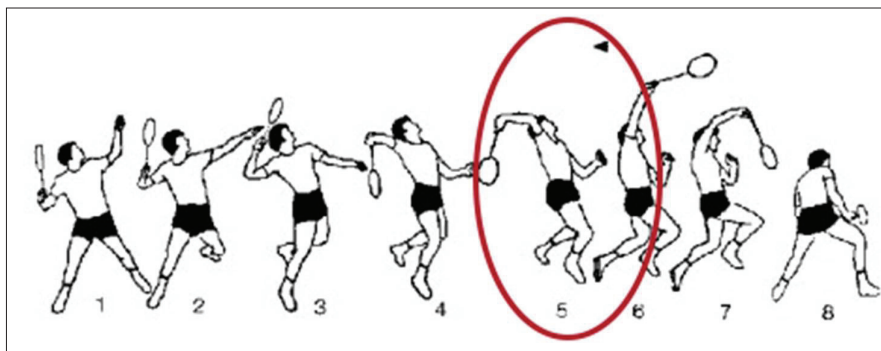   = | State 02 - State 03 | ≥ 15

Follow through

The dominant arm should make it to the very front, completing the rotation. Angle Between Dominant underarm -
(let elbow = E, shoulder = S, hip = H)
    = Angle ESH < 30
The dominant leg should be in front of the body. The non-dominant leg should be behind. -
(let ankle = A, hip = H, non dominant hip = H')
    = Angle AHH' ≥ 90

These mathematical conditions, which satisfy the ideal biomechanics of the smash shot, are based on the theoretical definition given by Putra & Lumintuarso (2020) on the biomechanical principle of the forehand smash in badminton, as well as a YouTube tutorial on smash and clear by Wadenka (2019), a professional badminton player from Germany.
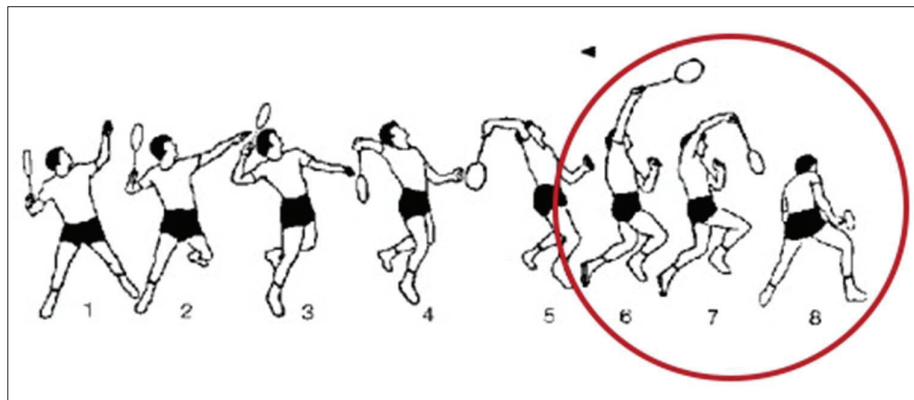

Figure 6: Smash phase - Follow through (Available at: https://jordynhealy.wordpress.com/biomechanical-analysis/)

Key points used for the features of the simple dynamic model

To calculate the mathematical relationships between the body joints and identify the ideal biomechanics for a forehand smash, the researchers have decided to focus on the 12 key points (pose landmarks) highlighted in Figure 7 based on the theoretical description of the ideal biomechanics.

Ten different angles based on the 12 skeletal points, including the right and left elbow angles, right and left underarm angles, right and left leg angles, right and left chest angles, and right and left wrist angles will be calculated.

Deriving the angle between coordinates in degrees using the law of cosines

The Law of Cosines, as shown in Figure 8, is a mathematical formula used to find the lengths of the sides and the measures of the angles of a non-right triangle.

In mathematical notation, the Law of Cosines can be expressed as equation (1):

$$(Distance(A, C))^2 = (Distance(A, B))^2 + (Distance(B, C))^2$$
$$- 2(Distance(A, B))(Distance(B, C)) \cos(\theta)$$

...(1)
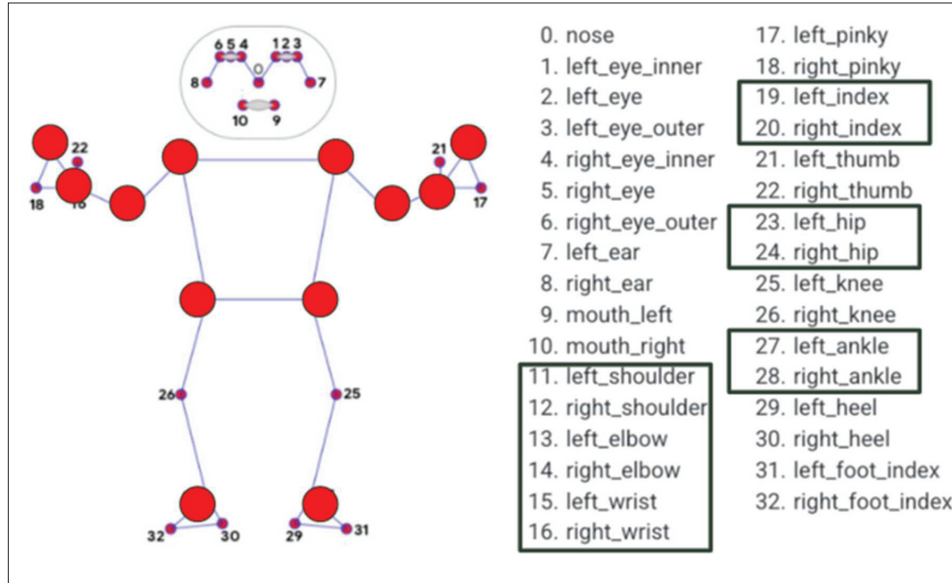
Figure 7:   12 Key points mainly focused on this research (Available at: https://github.com/google/mediapipe/
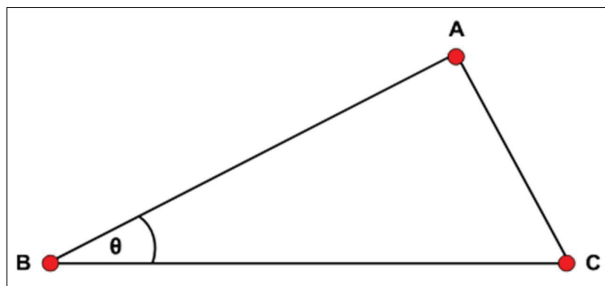blob/master/docs/solutions/pose.md)

Figure 8:   A triangle depicting the Law of Cosines

where Distance(A,C) is the length of the side opposite the angle, and Distance(A,B) and Distance(B,C) are the lengths of the other two sides of the triangle, and θ is the angle opposite to the side Distance(A,C).

In the study, the researchers utilize the Law of Cosines to compute the angle between three three-dimensional skeletal points. This calculation is intended to assess the degree of deviation between the skeletal points obtained from two distinct perspectives. The equation will be suitably adapted to account for this purpose, as following equation (2):

$$\cos(\theta) = \frac{(Distance(A,B))^2 + (Distance(B,C))^2 - (Distance(A,C))^2}{2 \times Distance(A,B) \times Distance(B,C)} \quad ...(2)$$

Now, the distance between two points in a three-dimensional space can be calculated using the Pythagorean Theorem, which states that the square of the hypotenuse of a right-angled triangle is equal to the sum of the squares of its two other sides. In a 3D space, the distance between two points (x_1, y_1, z_1) and (x_2, y_2, z_2) can be found using the following formula (3):

$$Distance = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2 + (z_2 - z_1)^2} \quad ...(3)$$

This formula involves finding the difference between the coordinates of the two points in each dimension, squaring them, adding them together, and then taking the square root of the sum to obtain the distance. Using this formula, we can derive the distances in between three 3D coordinates A, B and C as following equations:

$$Distance(A,B) = \sqrt{(x_B - x_A)^2 + (y_B - y_A)^2 + (z_B - z_A)^2}$$

$$Distance(B,C) = \sqrt{(x_C - x_B)^2 + (y_C - y_B)^2 + (z_C - z_B)^2}$$

$$Distance(A, C) = \sqrt{(x_C - x_A)^2 + (y_C - y_A)^2 + (z_C - z_A)^2}$$

After substituting the values from the distance formula into the modified formula of the law of cosines, the angle between the three 3D points can be obtained by applying the following formula (4):

Angle in between three 3D points = $\cos^{-1}(\cos(\theta))$ ...(4)

It is important to note that this angle will be represented in radians. To convert the angle value from radians to degrees, the following formula will be applied as in (5):

Angle in degrees = $\left| \theta \times \dfrac{180}{\pi} \right|$, where θ is in radians. ...(5)

By applying the above formula, the angle in degrees can be calculated, which can be used to determine the deviation between the skeletal points extracted from two different perspectives.

Data collection and preprocessing techniques: on-site data collection

For data collection, the researchers approached a segment of university-level badminton players consisting of 12 right-handed male players, as recommended by the badminton coach of the University of Colombo (UoC). After obtaining consent, each player was requested to play a rally of forehand smash shots, which were then recorded using a Redmi Note 10 Pro smartphone camera. The rallies were recorded in 1080p resolution and at a rate of 30 frames per second.
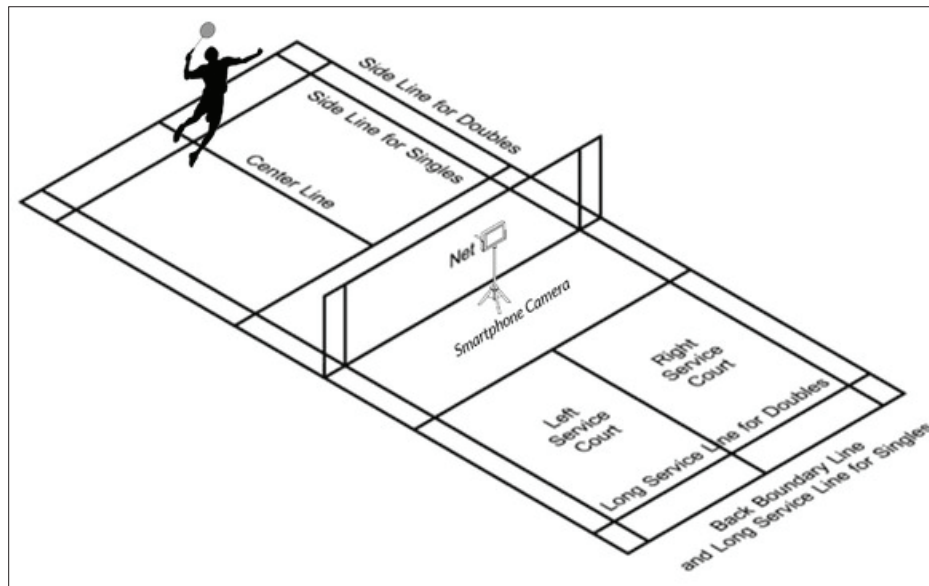

Figure 9: Field setup (Available at: https://commons.wikimedia.org/wiki/File:Badminton_court_3d_ small.png)

Field setup and training protocol followed prior to on-site data collection

The smartphone camera, securely mounted to a tripod, was strategically positioned at the center and in front of the badminton court net to record the player's full-body movements as shown in figure 9. After comparing skeletal coordinates extracted from various angles, the decision was made to front-face the camera. This orientation captures all necessary skeletal points of the player, as MediaPipe relies on face recognition to map

the remaining coordinates in the body. Next, every right-handed player faced the smartphone camera while another player in the opposite end of the court shot 15-20 shuttlecocks one after the other, allowing the first player to perform forehand smashes towards the incoming shuttlecocks. Imperfect smash shots in the rallies would then be evaluated by the badminton coach. The coach viewed recorded shots individually, assisting the research team in categorizing perfect smashes and discarding the rest.

Data preprocessing

The recorded videos were cropped to a 1:1 aspect ratio and the 12 rallies were segmented into 227 short clips of individual smash shots using Adobe Premiere Pro Creative Cloud (CC) 2019. These were then exported as separate videos. These videos were later reviewed by the domain expert, who assisted in accurately classifying the shots as either 'smash' or 'non-smash.' Some of the 'smash' shots that were identified by the badminton coach as perfect were used to evaluate the accuracy of the proposed Simple Dynamic model.

Normalizing the video clips to 100 frames

After careful observation, it was noted that while the duration of a badminton forehand smash shot may vary among players, it was determined that normalizing the video clip of a shot to 100 frames would be appropriate. This would ensure that the processed video would have a length of 3 seconds plus 10 frames, given a frame rate of 30 frames per second. This approach would allow for a more accurate evaluation of the biomechanics of the forehand smash shot, as each stage of the shot would be represented proportionally across all shots.

Development of a player-to-player comparison model

A player-to-player comparison model is developed by comparing angle values obtained from the biomechanical analysis of two different players' forehand smash shots. This model calculates and visually represents the deviation between these angle sets, providing a valuable tool for coaches to assess player performance or for players to self-evaluate.

To achieve this, angle values from a reference video showcasing the ideal forehand smash were extracted and saved in a CSV file, as were angle values from another player's body parts. Both videos underwent preprocessing and normalization to ensure consistent dimensions in the CSV files. The angle values from these files were imported into separate numpy arrays, and the deviation between them was calculated and stored in another array. This deviation data was then used to create a heatmap, which graphically illustrates differences between the angle sets and pinpoints areas for potential technique improvement in the player.

Building a machine learning model

By installing Mediapipe, OpenCV-python, Pandas Scikit-learn, the machine learning model will have access to the necessary tools to train and test models on data.

Detect skeletal points using Mediapipe

Computer vision and machine learning approaches were used to detect and track a person's body movements in real-time through a video feed. The Model first captures video passed, then initializes the Mediapipe Holistic model, which detects and tracks pose. Next, the model reads each frame from the captured video feed, and applies the Holistic model to it. The Holistic model then makes detections on the recoloured frame and identifies the position of each body part. The model then renders the body parts on it.

Capture landmarks and export to CSV

The pose landmarks are represented by a list of landmarks, each containing x, y, and z coordinates of the landmark, as well as a visibility measure for the landmark. The first column is named 'class' and the following columns are named in a sequential manner using a loop. The loop runs from 1 to 33, i.e the number of total skeletal coordinates (inclusive) and for each iteration, it appends four strings to the landmarks list: 'x', 'y', 'z', and 'v', along with the iteration number as a suffix. These four strings represent the x, y, z coordinates and the visibility of each landmark point. A total of 9017 frames extracted from the video footage dataset were divided into two classes, 'smash' and 'non smash', which have 5591 frames and 3426 frames each, respectively. Each frame has coordinates for 33 skeletal points. Each skeletal point has 3-dimensional coordinates and a visibility measure. So the total features in the data set are 33 x 4 = 132 features per frame. The target variable, called 'class', contains 2 classes as mentioned above.

Train custom model using Scikit Learn

The dataset is being preprocessed to create x and y, which will be used for training and testing the machine learning model. x is created by dropping the 'class' column from the dataset, while y is created by assigning the 'class' column of the dataset to the variable y, which will be used as the target variable for training and testing the machine

learning model, using the train test split method from the scikit learn library to split the data set into training and testing sets. In this case, the test data will contain 30% of the original data set, while the remaining 70% will be used for training.

Logistic regression and Ridge classifier are linear models, while the Random Forest classifier and Gradient Boosting classifier are tree-based models. The selection of machine learning models depends on this research problem which is to identify and evaluate the forehand standing smash shot, the nature of the data set which is very huge in the number of features to evaluate (132

features) and the specific objective of the research. In this case, since the target variable is categorical (*i.e.*, Smash or Non Smash), classification models would be more suitable than regression. It then fits the models using the training data and stores the models in the dictionary 'fit models'.

Make detections with model

After successfully training the model, new video footage was provided to the model as an input to check if the model accurately shows the probability of the played shot being a smash, as shown in Figure 10.

Figure 10: Trained machine learning model making detections

RESULTS AND DISCUSSION

Simple dynamic model

In this study, the biomechanical accuracy of the forehand smash shot in badminton was evaluated using two video clips of different players performing a perfect forehand smash. The clips were normalized to 100 frames and processed using a MediaPipe-powered Python

program, which calculated the angles between body parts. These angles were compared against predefined mathematical conditions mentioned earlier. The program outputted values of 1 or 0 based on whether the conditions were met or not, and the results were saved in a CSV file. The CSV file was then used to generate a graph as shown in Figure 11, where green indicated a value of 1 and red indicated a value of 0, representing the accuracy of the shot performed by player 1.
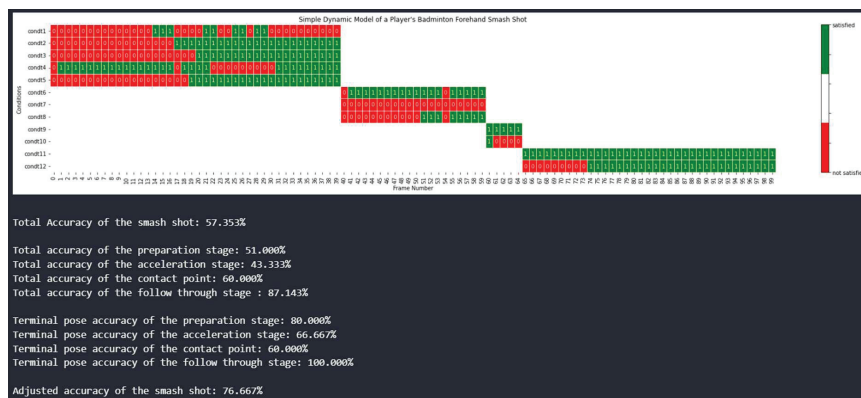

Figure 11: Colour-coded graph depicting the simple dynamic model of player 1 performing the shot

To assess the terminal pose accuracy of each phase, only the last 5 frames of each phase were considered. The accuracy of the terminal pose was calculated, and these values were cumulated to determine the overall accuracy of the entire forehand smash shot. The results were discussed with the domain experts, who confirmed the accuracy of the players' terminal poses based on their expertise.

The effectiveness of the simple dynamic model was further verified by testing it on player 2's video clip as shown in Figure 12, which also successfully aligned with the evaluation provided by the domain expert. Additionally, when compared with a video clip from a web source called Badminton TV, as shown in Figure 13, the model highlighted areas where the player needed to improve their technique at the follow-through stage.

Figure 12: Colour-coded graph depicting the simple dynamic model of player 2, to further confirm the accuracy of the model

Figure 13: Colour-coded graph depicting the simple dynamic model of a player footage that was extracted from the web

Player-to-player comparison model

The player-to-player comparison model for evaluating the biomechanical accuracy of the forehand smash shot in badminton involved selecting two video clips of different players. One video served as a reference for a perfect smash shot, while the other video was used to evaluate a player's technique by comparing it with the reference player. Both videos were normalized to 100 frames and processed using a MediaPipe-powered Python program to calculate the angles between body parts. The angle

values were saved in separate CSV files, which were then used to generate a graph.

The graph, depicted in Figure 14, visually represented the deviation between the angle values of the two players. The graph was colour-coded, with a range of colours between black and white, indicating the deviation in each cell. White represented negative deviation, while black represented positive deviation. Additionally, the graph was improved by further colour-coding to represent the four phases of the shot, enhancing the user experience.
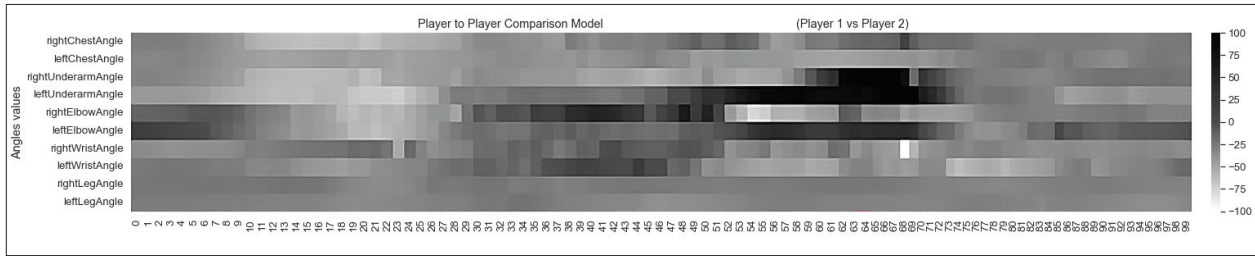
Figure 14: Colour-coded graph depicting the player-to-player comparison model
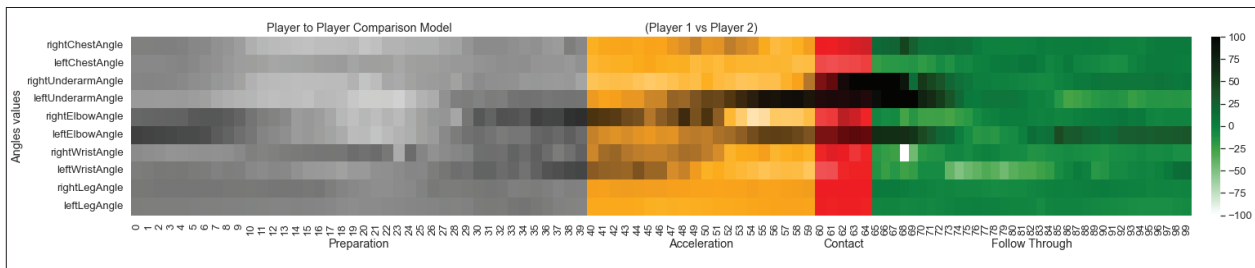

Figure 15: Colour-coded graph depicting the player-to-player comparison model, separated by phases

Figure 15 displays the graph showing the variation of deviation between angle values recorded by the two players at each frame of the video. This analysis demonstrated promising potential for assessing a player's biomechanics by comparing them to another player, providing valuable insights into their technique and performance.

Machine learning model

This research employed four types of machine learning (ML) models, namely logistic regression (LR), ridge classifier (RC), random forest classifier (RF), and gradient boosting classifier (GB), to analyze the data. To determine the best-performing model for this research, all the ML models were trained using a pipeline approach. Accuracy, F1 score, and the confusion matrix were utilized as evaluation metrics. The Confusion Matrix, derived from the results of all four algorithms, provided a comprehensive overview of the model's performance. Figure 16 represents the confusion matrix for each algorithm, where true positive (TP), false positive (FP), false negative (FN) and true negative (TN) values for respective models are shown.

		Predictions (System) - Logistic Regression				**Predictions (System) - Ridge Classifier**	
		Positive (Smash)	Negative (Smash)			Positive (Smash)	Negative (Smash)
Actual (Expert)	Positive (Smash)	TP = 1480	FN = 200	**Actual (Expert)**	Positive (Smash)	TP = 1532	FN = 148
	Negative (Smash)	FP = 457	TN = 569		Negative (Smash)	FP = 478	TN = 548
		Predictions (System) - Gradient Boosting				**Predictions (System) - Random Forest**	
		Positive (Smash)	Negative (Smash)			Positive (Smash)	Negative (Smash)
Actual (Expert)	Positive (Smash)	TP = 1611	FN = 69	**Actual (Expert)**	Positive (Smash)	TP = 1677	FN = 3
	Negative (Smash)	FP = 337	TN = 689		Negative (Smash)	FP = 71	TN = 955

Figure 16: Confusion matrices for LR, RC,GB and RF algorithms

Hyper parameter tuning for the selected classifiers

The purpose of hyper-parameter tuning is to enhance the model's performance on unseen data by avoiding over-fitting or under-fitting and improving its generalization ability. By optimizing the hyper-parameters, the model becomes better equipped to learn patterns from the training data and apply those patterns to new, unseen data.

Various methods can be employed for hyper-parameter tuning. In this research, hyper-parameter tuning was conducted using the random search method, and the results of the training process are presented in Figure 17.

The Simple Dynamic Model revealed that evaluating smash shots from a side view offers clearer insights into dominant arm movements, while a front view provides a better understanding of body rotation at the end of the shot. However, this research focuses on analyzing forehand smash shots from the front view since MediaPipe requires face detection to identify skeletal points. The study suggests a comprehensive methodology that incorporates multiple angles to assess and record player body movements, contributing to analysing the shot better.

The player-to-player comparison model serves multiple purposes. Firstly, it enables the comparison of a
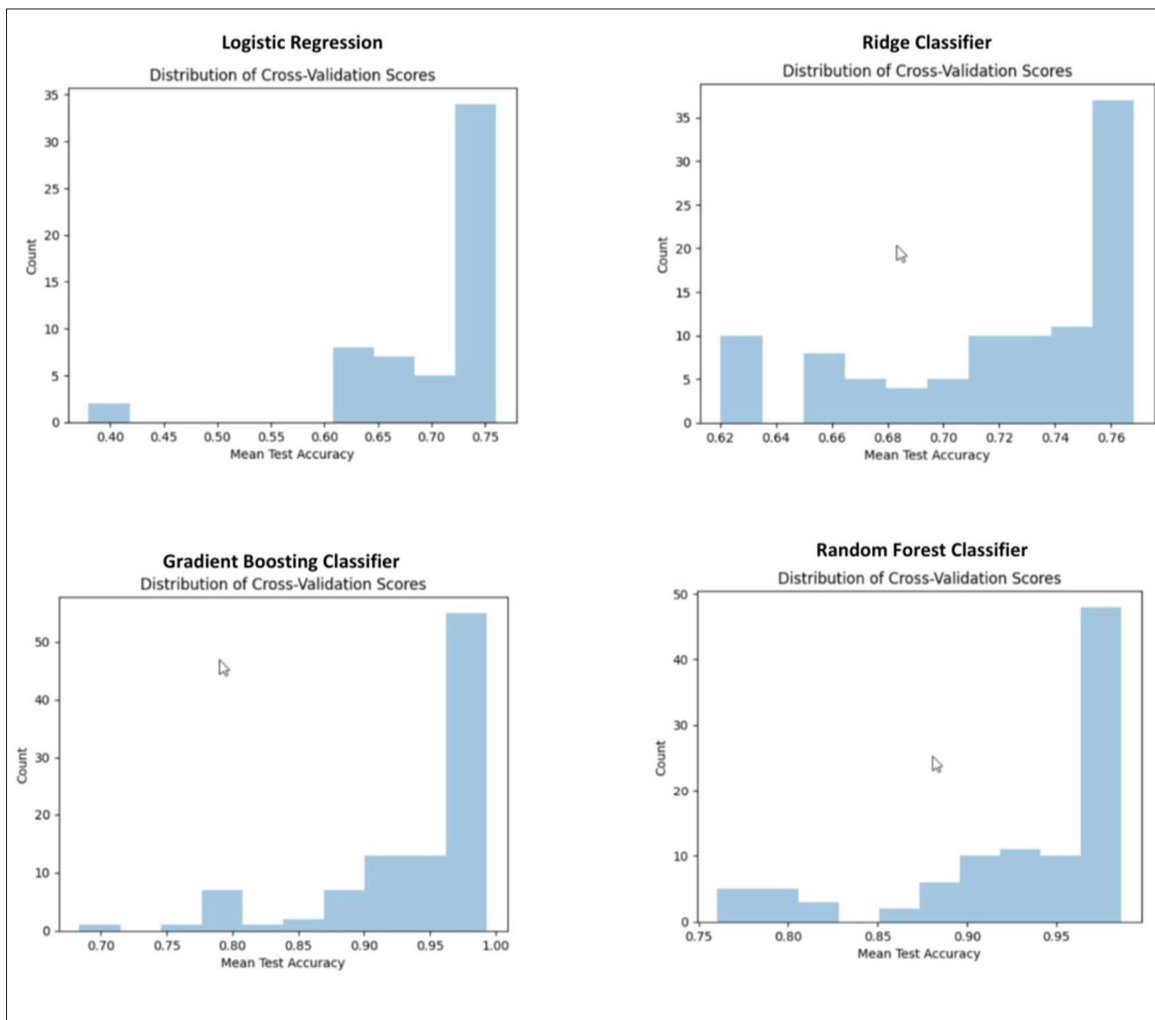

Figure 17: Distribution of cross-validation scores

player's performance by using an ideal performance as a reference, allowing for a qualitative assessment of their skills. Additionally, it facilitates the improvement of individual players by comparing their current performance with their previous ones, helping them identify areas of improvement. The model also provides valuable insights by analyzing the deviations between performances, allowing trainers and players to pinpoint specific areas that require correction or adjustment. Lastly, the model accommodates the evaluation of unorthodox approaches to playing the forehand smash, expanding the scope of analysis to include other playing styles.

After training all 4 models to determine the best performing classifier for the Machine Learning Model, various measures were found to identify the best model for this research purpose and the dataset we have used. Table 2 shows the overall comparison matrix.

Table 2: Overall Performance metrics

Classifier	Accuracy	Error rate	Precision	Recall	Specificity	FP rate	FN rate	F1 score
Logistic regression	0.757	0.243	0.764	0.881	0.556	0.445	0.119	0.818
Ridge classifier	0.769	0.231	0.762	0.912	0.534	0.466	0.088	0.830
Gradient boosting	0.849	0.150	0.827	0.959	0.672	0.328	0.041	0.887
Random forest	0.974	0.027	0.959	0.998	0.931	0.069	0.001	0.980

As shown in table 2, Random Forest Classifier outperformed the other 3 models by comparatively high margin. This is one of the reasons to choose a Random Forest Classifier as the best model for this research.

The cross-validation scores across the hyper-parameter search space for all 4 classifiers are listed below.
• Logistic Regression: 75.11%
• Ridge Classifier: 77.11%
• Gradient Boosting Classifier: 99.33%
• Random Forest Classifier : 98.73%

Approximate time taken for hyper-parameter tuning process is as follows.

• Logistic Regression : 2.5 hours
• Ridge Classifier: 1.5 hours
• Gradient Boosting Classifier: 9 hours
• Random Forest Classifier : 4.5 Hours

The results indicate that Logistic Regression and Ridge Classifier performed relatively poorly on the dataset used in this research. On the other hand, both Random Forest Classifier and Gradient Boosting Classifier showed high accuracy scores, with little difference between them. However, it is important to note that the hyper-parameter tuning process took nearly double the time for the Gradient Boosting Classifier compared to the Random Forest Classifier. Considering these factors, the Random Forest Classifier was chosen as the best-performing algorithm for this study.

In the initial stage of the research, videos from university-level badminton players and "Badminton World TV" YouTube videos were used to train the model. This resulted in a 100% accuracy for all four models. However, further investigation revealed that the dataset contained both smash and non-smash shots from different sources, leading to this perfect accuracy. To address this, the dataset was reproduced using only manually recorded videos, including non-smash shots recorded with the help of university-level badminton players. Initially, the model provided an output for each frame, indicating whether it was a smash or non-smash shot and the corresponding probabilities. Later, it was modified to only display the probability of being a smash shot.

There were issues with extracting skeletal points using Mediapipe, as some frames had low visibility or flickering, resulting in missing or incorrect coordinate records in the CSV file. Also, training the model by dividing the smash shot into phases was unsuccessful due to the clip duration being too small for MediaPipe.

Recommendations, limitations, and future directions

Based on the research findings, several recommendations are proposed to enhance the evaluation of badminton forehand smash shots and improve player performance assessment. Firstly, it is recommended to use the developed Simple Dynamic Model and Player-to-player Comparison Model for evaluating single-player rallies, offering systematic approaches for assessing shot

accuracy, particularly under orthodox conditions or with players of unorthodox styles.

The recording of shots at a frame rate of 30 fps may not capture all the intricate details of the shot, resulting in blurred body images and potentially impacting the visibility of the detected skeletal points by MediaPipe, leading to inaccurate results. To address this, using a higher frame rate and normalizing frames to a larger number can be considered, although it may affect the processing speed, particularly on hardware with limited specifications. Therefore, a balance must be struck between accuracy and processing speed when selecting parameters for the program. At the moment, to ensure compatibility with these models and Mediapipe technology, it is advised to use video clips with a frame rate of 30 fps or lower and shots recorded in the front view.

The research also has other limitations, including the focus on the front angle, visibility issues, and challenges in machine learning model training. Future research can be expanded to include diverse player demographics, other types of smash shots, and additional badminton shot evaluations. Improvements in technology, accurate shot phase prediction, and the inclusion of shot intensity as an assessment feature are suggested.

Furthermore, evaluating two-player rallies to assess team performance and doubles play dynamics is recommended to provide a more comprehensive understanding of badminton performance. These recommendations and future research directions aim to broaden the scope of analysis and contribute to comprehensive assessment frameworks in badminton.

CONCLUSION

This research introduces a cost-effective method for athletes to independently assess their badminton smash shot performance, reducing reliance on external resources or expertise. Simultaneously, it offers coaches a streamlined, data-driven approach to evaluate players during forehand smash shots, minimizing subjectivity for more accurate feedback. The proposed methodology eliminates the need for extensive manual analysis and external peripherals, thereby reducing the resources required for performance assessment. The simple dynamic model described in this research is the first of its kind, as this is the first attempt to quantitatively describe a badminton shot. The study makes a significant contribution to the badminton performance analysis domain.

REFERENCES

Adesida Y., Papi E. & McGregor A.H. (2019). Exploring the role of wearable technology in sport kinematics and kinetics: A systematic review. *Sensors* **19**(7): 1597.
DOI: https://doi.org/10.3390/s19071597

Alderson J. (2015). A markerless motion capture technique for sport performance analysis and injury prevention: Toward a 'big data', machine learning future. *Journal of Science and Medicine in Sport* **19**: e79.
DOI: https://doi.org/10.1016/j.jsams.2015.12.192

Ananth S.V., Patawari A., Sundari K., Raghavi, Likitha S., & Arivalagan S. (2019). Biomechanical Sports Analysis Using Inertial Measurement Unit. *2019 IEEE International Conference on System, Computation, Automation and Networking (ICSCAN)* 29-30 March. Pondicherry, India, pp. 1–5.
DOI: 10.1109/ICSCAN.2019.8878691

Bartlett R. (2021). *Introduction to Sports Biomechanics: Analysing Human Movement Patterns,* 2nd edition. Routledge, London, United Kingdom.
DOI: https://doi.org/10.4324/9781315889504

Bazarevsky V., Grishchenko I., Raveendran K., Zhu T., Zhang F. & Grundmann M. (2020). BlazePose: On-device real-time body pose tracking. *arXiv preprint arXiv:2006.10204.*
DOI: https://doi.org/10.48550/arXiv.2006.10204

Cao Z., Hidalgo G., Simon T., Wei S. & Sheikh Y. (2021). OpenPose: Realtime multi-person 2D pose estimation using part affinity fields. *IEEE Transactions on Pattern Analysis & Machine Intelligence* **43**(1): 172–186.
DOI: 10.1109/TPAMI.2019.2929257

Chu W. & Situmeang S. (2017). Badminton video analysis based on spatiotemporal and stroke features. *Proceedings of the 2017 ACM on International Conference on Multimedia Retrieval*, Bucharest, Romania, 6-9 June. Association for Computing Machinery, New York, NY, USA, pp. 448–451.
DOI: https://doi.org/10.1145/3078971.3079032

Chung J., Ong L. & Leow M. (2022). Comparative analysis of skeleton-based human pose estimation. *Future Internet* **14**(12): 380.
DOI: https://doi.org/10.3390/fi14120380

Fang H.S., Li J., Tang H., Xu C., Zhu H., Xiu Y., Li Y.L. and Lu C. (2022). AlphaPose: Whole-body regional multi-person pose estimation and tracking in real-time. *IEEE*

Transactions on Pattern Analysis and Machine Intelligence **45**(6): 7157–7173.
DOI: 10.1109/TPAMI.2022.3222784

Ghani D.Z.A., Zainuddin Z.A. & Ibrahim H. (2019). Squash backhand stroke analyses for three different playing levels in Malaysia. *Proceedings of the 3rd International Colloquium on Sports Science, Exercise, Engineering and Technology* (eds. Sulaiman N., Ismail S. & Adnan R.), Singapore. Springer, Singapore, pp. 17–23.
DOI: https://doi.org/10.1007/978-981-10-6772-3_3

Ghazali N. F., Shahar N. & As'ari M.A. (2022). Badminton strokes recognition using inertial sensor and machine learning approach. *2022 2nd International Conference on Intelligent Cybernetics Technology and Applications* (ICICyTA), Bandung, Indonesia. IEEE, pp. 1–5.
DOI: 10.1109/ICICyTA57421.2022.10037897

He S. & Gong R. (2022). Recognition and prediction of badminton attitude based on video image analysis. *Mobile Information Systems* **2022**: 1–9.
DOI: https://doi.org/10.1155/2022/6960343

Hsueh Y., Chen Y., Pan K. and Tsai C. (2012). Biomechanical analysis of badminton forehand net shots. *30th Annual Conference of Biomechanics in Sports*, Melbourne, Australia. pp. 256–259.

Ju N., Yu D., Ik T. & Peng W. (2020). Trajectory-based badminton shots detection. *2020 International Conference on Pervasive Artificial Intelligence (ICPAI)*, 3-5 December. Taipei, Taiwan, IEEE, pp. 64–71.
DOI: 10.1109/ICPAI51961.2020.00020

Kurnia R., Pasmai A. & Elfitri I. (2020). Analysis of the smash and dropshot movement patterns in badminton sports using Pearson correlation. *Proceedings of the 2020 10th International Conference on Biomedical Engineering and Technology (ICBET '20)*, Tokyo, Japan. Association for Computing Machinery, New York, NY, USA, pp. 164–169.
DOI: https://doi.org/10.1145/3397391.3397434

Liu F. & Sun Y. (2022). A Tracing-based Tennis coaching and smart training platform using artificial intelligence and computer vision. Artificial intelligence and fuzzy logic system. *8th International Conference on Artificial Intelligence and Fuzzy Logic System (AIFZ 2022)* (eds. Wyld D.C. & Nagamalai D.), Toronto, Canada, 24–25 September. Academy and Industry Research Collaboration Center (AIRCC), pp. 89–100.
DOI: https://doi.org/10.5121/csit.2022.121608

Lu T. & Chang C. (2012). Biomechanics of human movement and its clinical applications. *The Kaohsiung Journal of Medical Sciences* **28**(2): S13–S25.
DOI: https://doi.org/10.1016/j.kjms.2011.08.004

Nakano N., Sakura T., Ueda K., Omura L., Kimura A., Iino Y., Fukashiro S. & Yoshioka S. (2020) Evaluation of 3D markerless motion capture accuracy using openpose with multiple video cameras. *Frontiers in Sports and Active Living* **2**: 50.
DOI: 10.3389/fspor.2020.00050

Putra G.E. & Lumintuarso R. (2020). What is the Biomechanical principle of forehand smash in badminton? *Physical Education and Sport Through the Centuries* **7**: 221–229.
DOI: https://doi.org/10.2478/spes-2020-0018

Rahmad N.A., As'ari M.A., Soeed K. & Zulkapri I. (2020). Automated badminton smash recognition using convolutional neural network on the vision based data. In: IOP Conference Series: Materials Science and Engineering. *Sustainable and Integrated Engineering International Conference 2019 (SIE 2019)* 8–9 December. The Everly Putrajaya, Putrajaya, Malaysia, pp. 1–8.
DOI: 10.1088/1757-899X/884/1/012009

Rusdiana A., Abdullah M.R.B., Syahid A.M., Haryono T. & Kurniawan T. (2021a). Badminton overhead backhand and forehand smashes: a biomechanical analysis approach. *Journal of Physical Education and Sport* **21**(4): 1722–1727.
DOI: 10.7752/jpes.2021.04218

Rusdiana A., Subarjah H., Badruzaman B., Budiman D., Wibowo R., Nurjaya D.R., Pramutadi A., Mustari A., Kusdinar Y. & Syahid A. (2021b). Kinetics analysis of overhead standing smash in badminton. *Jurnal Pendidikan Jasmani dan Olahraga* **6**(1): 81–88.
DOI: https://doi.org/10.17509/jpjo.v6i1.32577

Rusdiana A., Subarjah H., Imanudin I., Kusdinar Y., Syahid A.M. & Kurniawan T. (2020). Effect of fatigue on biomechanical variable changes in overhead badminton jump smash. *Annals of Applied Sport Science* **8**(s1): e895.
DOI: http://dx.doi.org/10.29252/aassjournal.895

Salim M.S., Lim H.N., Salim M.S.M. & Baharuddin M.Y. (2010). Motion analysis of arm movement during badminton smash. *2010 IEEE EMBS Conference on Biomedical Engineering and Sciences (IECBES)* 30 November - 02 December. Kuala Lumpur, Malaysia, IEEE, pp. 111–114.
DOI: 10.1109/IECBES.2010.5742210.

Sharma M., Anand A., Srivastava R. & Kaligounder L. (2018). Wearable Audio and IMU based shot detection in racquet sports. *arXiv preprint arXiv:1805.05456.*
DOI: https://doi.org/10.48550/arXiv.1805.05456

Tan D.Y.W., Ting H.Y. & Lau S.B.Y. (2016). A review on badminton motion analysis. *2016 International Conference on Robotics, Automation and Sciences (ICORAS)* 5-6 November. Melaka, Malaysia, IEEE, pp. 1–4.
DOI: 10.1109/ICORAS.2016.7872604

Torres-Luque G., Cabello-Manrique D., Hernández-Garcia R. & Garatachea N. (2011). An analysis of competition in young tennis players. *European Journal of Sports Science* **11**(1): 39–43.
DOI: https://doi.org/10.1080/17461391003770533

Tsai C., Chang S. & Huang C. (1998). Biomechanical analysis of differences in the badminton smash and jump smash between Taiwan elite and collegiate players. *XVI International Symposium on Biomechanics in Sports* (eds. Riehle H. & Vieten M.M.), University of Konstanz, Germany. UVK-Universitätsverlag Konstanz, Konstanz, Germany, pp., 259–262.

Vora V., Arora M. and Ranawat D. (2018). Biomechanics in badminton - A review. *Orthopedics and Sports Medicine: Open Access Journal* **2**(1): 114–116.

Wadenka T. (2019). Smash and clear tutorial: Get more power

in your overheadshots. Available at *https://www.youtube.com/watch?v=HvAOMnoT3zQ* , Accessed 4 January 2023.

Wang C., Bochkovskiy A. & Liao H.M. (2022). YOLOv7: Trainable bag-of-freebies sets new state-of-the-art for real-time object detectors. *2023 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, Vancouver, BC, Canada, 17-24 June. IEEE, pp. 7464–7475.

Williams B. K., Sanders R. H., Ryu J. H., Graham-Smith P. & Sinclair P. J. (2021). Racket orientation angle differences between accurate and inaccurate squash shots, as determined by a racket embedded magnetic-inertial measurement unit. *Sports Biomechanics* 1–13.
DOI: https://doi.org/10.1080/14763141.2021.1892175

Ying Y.Z., Khairuddin I.M., Isa W.H.M., Majeed A.P.P.A., Abdullah M.A. & Razman M.A.M. (2022). Badminton smashing recognition through video performance by using deep learning. *Mekatronika* **4**(1): 70–79.
DOI: https://doi.org/10.15282/mekatronika.v4i1.8607

Zeng H. & Zhao Y. (2011). Sensing movement: microsensors for body motion measurement. *Sensors* **11**(1): 638–660.
DOI: https://doi.org/10.3390/s110100638

Zhang Z., Li S., Wan B., Visentin P., Jiang Q., Dyck M., Li H. & Shan G. (2016). The influence of X-factor (trunk rotation) and experience on the quality of the badminton forehand smash. *Journal of Human Kinetics* **53**(1): 9–22.
DOI: 10.1515/hukin-2016-0006