ARTICLE IN PRESS

Journal of Engineering Research xxx (xxxx) xxx

Contents lists available at ScienceDirect

Journal of Engineering Research

journal homepage: www.journals.elsevier.com/journal-of-engineering-research

Using artificial intelligence to predict the next deceptive movement based on video sequence analysis: A case study on a professional cricket player's movements

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ARTICLE INFO

Keywords:
Artificial intelligence
Deceptive movements
Machine learning
Cricket
Performance optimization

ABSTRACT

This research develops an artificial intelligence-based model to predict the next deceptive movement of athletes by analyzing video sequences of previous movements. Utilizing advanced deep neural network models, we analyze deceptive movements to forecast the next move, with a practical application on the deceptive movements of a professional cricket player. The model employs machine learning techniques such as Random Forest (RF), Decision Trees (DT), and K-Nearest Neighbor (KNN) to enhance prediction accuracy. Achieving up to 70 % accuracy, this model rivals human capability, as even highly skilled players can easily fall for deceptive actions. The ability to predict deceptive movements sets humans apart from many intelligent creatures, allowing athletes to avoid predictable actions and gain an edge in various sports. This study applies this concept to cricket, leveraging video data to improve training methods. The results highlight the potential of artificial intelligence in revolutionizing training and performance optimization in sports.

Introduction

Deceptive behavior is a hallmark of high intelligence, distinguishing humans from many other intelligent creatures. This ability to execute and predict deceptive movements is especially crucial in sports, where athletes use such actions to outsmart their opponents. For instance, in football, players often employ deceptive maneuvers when passing a member of the opposing team or during penalty kicks to mislead the goalkeeper. These sophisticated actions involve a sequence of movements that appear to follow a predictable pattern, only to be altered at the last moment, making them difficult to anticipate.

The biomechanics of bowling in cricket has been a topic of significant research, focusing on understanding and optimizing performance while reducing injury risks. Studies have highlighted the kinematic and kinetic aspects of bowling, emphasizing body position, arm action, wrist alignment, and footwork in delivering deceptive movements [81]. Spin bowling, in particular, remains underexplored, with researchers emphasizing the complexity and skill required to achieve deceptive spin deliveries [82,83] further analyzed spin bowling mechanics, identifying key biomechanical variables that influence performance and deception. Similarly, studies on fast bowling have revealed the nuanced differences between skilled and amateur players, showcasing the role of advanced techniques in executing deceptive actions [84]. A biomechanical model by [85]. demonstrated the dynamics of bowling arms and their contributions to deceptive deliveries. Additionally, the use of biomechanics in evaluating the legality of bowling actions has provided insights into how deceptive techniques can be optimized while adhering to regulatory guidelines [86]. These studies collectively underline the need for advanced analytical models, such as the use of artificial intelligence, to further investigate and improve deceptive movements in cricket.

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https://doi.org/10.1016/j.jer.2025.01.007
Received 22 September 2024; Received in revised form 4 January 2025; Accepted 19 January 2025
Available online 26 January 2025

Please cite this article as: A.M. Mutawa et al., *Journal of Engineering Research,* https://doi.org/10.1016/j.jer.2025.01.007

The capacity to predict these deceptive movements provides a significant advantage in competitive sports, enabling athletes to avoid predictability and maintain an edge over their opponents. This study focuses on leveraging artificial intelligence to predict the next deceptive movement of athletes by analyzing video sequences of their previous movements. By utilizing advanced deep neural network models and machine learning techniques such as Random Forest (RF), Decision Trees (DT), and K-Nearest Neighbor (KNN), we aim to forecast the next movement with high accuracy

The choice of cricket for this study is driven by the unique skills exhibited in the sport, setting it apart from many others. Unlike football, where players' deceptive actions such as passing a ball involve numerous dynamic factors like the angle of approach of the opposing team member, the position and location of the ball, and the spatial arrangement of all players, cricket offers a more controlled environment. In football, these variables add complexity and require extensive handling and training. Even in scenarios like penalty kicks, while many variables are constant, the primary focus is on the angle of contact, speed of the kick, and the player's eye and body posture.

Cricket provides a more straightforward yet rich context for studying deceptive movements. Many variables in cricket are constants, reducing the number of factors to be managed compared to football. For instance, in cricket, the ball is in motion with the player, making it a dynamic yet relatively controlled scenario. This controlled complexity allows for a focused study on the biomechanics and predictive modeling of deceptive movements in cricket. Additionally, cricket's distinct phases of play and the well-defined roles of players provide clear data points for analysis, making it an ideal case study for this research.

Applying this concept to cricket, we analyze a professional cricket player's deceptive movements, demonstrating our approach's practical application and effectiveness. The ability to predict deceptive movements is a testament to human intelligence and a skill that many highly skilled players can find challenging, as they can easily fall for deceptive actions.

In this study, we have developed a computer vision-based approach for estimating the bowler's stance *during delivery strides*, a significant accomplishment. A combination of image processing, feature extraction, and machine learning is used in the proposed system to analyze bowler posture and provide feedback on areas that need improvement [1]. The use of AI technology can improve training regimens and performance for coaches and players. A bowler's bowling angles can be analyzed by comparing posture shifts between runs conceded and wickets taken, and video recordings of their bowling angles can be analyzed. Bowlers should be aware of any differences in posture that may affect their performance. A proposed system compares angles between body parts for bowls that result in runs scored and bowls that result in wickets taken using video analysis tools to determine the posture of the bowler during the delivery stride. It aims to provide insights into the areas in which the bowler needs to improve so that he or she can perform better and allow fewer runs to be given up.

Deceptive movements in cricket are deliberate actions designed to mislead the opponent, gaining a strategic advantage in the game. These movements involve subtle biomechanical variations, timing alterations, and situational awareness, making them crucial to the psychological and tactical aspects of cricket. For bowlers, deceptive techniques may include changing the seam position or grip to alter the ball's trajectory, varying the pace of delivery to disrupt the batsman's timing, or using angles and actions to confuse the batsman about the line and length of the ball. Similarly, batsmen employ deceptive movements by using body feints to mislead bowlers or fielders, such as pretending to play a lofted shot but executing a soft push for a single or altering foot positioning to disguise shot intentions. Fielders, too, use deceptive strategies, such as feigned movements to lure batsmen into making risky runs. Beyond these physical tactics, deceptive movements often involve psychological elements [87], such as setting up patterns in deliveries or fielding placements to condition opponents into expecting specific actions, only to surprise them with an unexpected play. These integrated physical and mental strategies challenge players' skill, adaptability, and real-time decision-making. In modern cricket, leveraging AI to analyze and predict these movements offers significant potential to enhance coaching, training, and competitive strategies, particularly in high-stakes scenarios like IPL matches or international games.

This paper aims to integrate sports and technology by utilizing AI and machine learning algorithms to analyze and forecast intricate athletic movements. It employs vision techniques to examine the bowlers' body posture angles and variations during delivery strides. Through a detailed analysis of deceptive movements in cricket, we present a thorough case study demonstrating our approach's efficacy and its potential to improve athletic performance and minimize the likelihood of injuries. By focusing on deceptive movements in cricket, we provide a comprehensive case study that illustrates the effectiveness of our approach and its implications for enhancing athletic performance and reducing injury risks.

Research motivation

This study is motivated by the need to delve deeper into the symmetry and asymmetry of cricket bowlers' techniques *during delivery strides*, an area not adequately addressed by current pose estimation methods. Utilizing the surge in sports video data, this research applies a deep neural network for advanced 3D pose estimation, focusing on the intricate symmetrical and asymmetrical aspects of a bowler's body during delivery strides, arms, and hands. The primary goal is to enhance understanding and improve performance by accurately analyzing a bowler's bowling angles and postural variations, which are integral in identifying the balance between symmetry and asymmetry in their techniques.

Technical terms

Pose Estimation: A computational approach to identify and track the positions of key body parts during movements. It helps analyze an athlete's posture, which is essential for evaluating performance and identifying potential areas of improvement [88].

Symmetry and Asymmetry: In biomechanics, symmetry refers to balanced and consistent movements across the body, while asymmetry indicates deviations that might impact performance or increase the risk of injury [89].

Deep Neural Networks (DNNs): A class of machine learning algorithms designed to mimic the human brain's neural networks. DNNs are particularly effective for analyzing complex datasets like video sequences of sports movements [90].

Random Forest (RF) and K-Nearest Neighbor (KNN): These machine learning algorithms are commonly used for classification and regression tasks. In this study, they help predict postural changes and analyze the suitability of different models for sports analytics [91,92].

This study uses a deep neural network to determine 3D poses by estimating 3D shapes. A bowler's body, arms, and hands are monitored during delivery strides by the designed model so coaches and players can identify potential areas for improvement in their bowling technique. A significant contribution of this work lies in assessing a bowler's bowling angles and postural variations, which are crucial in identifying a bowler's technical strengths and limitations. It is beneficial for coaches and players alike to examine bowling techniques closely, as it enables them to make well-informed choices that improve their overall performance.

Human expert selection criteria

This study examines a world-leading cricketer's bowling methodology. The objective is to extract pertinent data points from his bowling footage using OpenCV and Open Pose estimation algorithms. A study focusing on a specific bowler and analyzing their performance could help improve their technique. This methodology enables a thorough evaluation of the proposed deep neural network-based 3D pose estimation model, along with its implications for understanding human expert bowling technique and physical fitness.

For this study, we have chosen Umran Malik, who is in the Indian Premier League (IPL), as our human expert. Malik is gaining attention with his impressive bowling speed (up to 154 KPH) [2] skills that draw the attention and interest of spectators, analysts, and organizational leadership [3]. Additional parameters like line and length, swing, seam control, accuracy, variations, and mental strength are crucial to maintaining consistency in cricket- bowling. A study was conducted to observe Umran Malik's performance in the 2022 and 2023 IPL and analyze it to support Malik and a number of young stars from this perspective [4].

The posture recognition system and methodology can be extended to assess and improve other bowlers' proficiency. Furthermore, it is noteworthy that the bowler's performance in current conditions is subject to daily fluctuations, making it likely that the deliberate choice to focus on a single bowler is intended to provide a comprehensive case study and highlight the potential benefit of the proposed system [5].

Major contributions

The research focuses on significant contributions, which are as follows:

- Using video clips as input sources, the study develops a deep learning algorithm to accurately predict the bowler's 3D pose during their bowling motion. It emphasizes the analysis of symmetric and asymmetric movements in cricket bowling during delivery strides. This model effectively addresses the limitations of existing pose estimation techniques, enabling accurate monitoring of the bowler's body, hands, and arms.
- This study utilizes empirical data obtained from a professional bowler to illustrate the practical and pertinent nature of the framework. Relevant data points are extracted from Umran Malik's bowling clips. This data serves as a basic groundwork for examining and evaluating the proposed framework for 3D pose estimation.
- We compared the efficacy of RF and KNN models in predicting postural changes. The discovery offers valuable insights into the suitability of machine-learning algorithms for analyzing bowling postures during delivery strides and reveals other significant research findings in the field.
- The study emphasizes the potential for utilizing the posture recognition system developed as a Virtual Coach. The system's ability to accurately measure bowling angles and postural adjustments during delivery strides makes it a valuable tool for coaches and players to pinpoint potential improvement areas. By incorporating it into the study, a virtual coach could potentially enhance training, refine technique, and optimize cricket performance.
- The study not only tackles the limitations related to pose estimation but also significantly contributes to the progress of sports analysis and computer vision. This paper presents a novel approach for accurately determining the 3D positions of objects, demonstrates the effectiveness of machine learning algorithms, and provides a practical implementation in the form of a posture recognition system that has the potential to revolutionize coaching and training in the sport of cricket.

The subsequent sections of the paper are structured as follows: Section 2 addresses the literature review, followed by an explanation of the materials and methods in Section 3. Section 4 presents the results and discussion, followed by conclusions in Section 5.

Literature review

The application of artificial intelligence (AI) and machine learning (ML) in sports, particularly cricket, has seen significant advancements [6,7]. The following literature review synthesizes key findings from several pivotal studies to highlight the progress and challenges in this field.

During international cricket, batsmen aim to score maximum runs without losing their wickets, while bowlers aim to dismiss them [8]. When bowling limited-overs games, a bowler may also try to stop the batsman from scoring and get the batter out since the bowler will concede fewer runs while experimenting with getting the batter out. The stance of a cricket bowler should be observed when he or she delivers a ball [9]. An AI-based model can predict posture changes based on bowling angles and postural body movements. Based on the video, time-stamped delivery information, GPS, and inertial sensor data, a random forest algorithm was trained by [10] to recognize rapid bowling deliveries in elite cricket matches. Combined with various data sources, machine learning approaches demonstrate their effectiveness in recognizing deliveries, providing fast bowlers with insight into their performance and injury prevention. A vital part of creating intelligent virtual coaches with AI models consists of recognizing crucial body regions without omitting any and maintaining the model's efficacy when body parts overlap [11,12]. It is imperative to provide each suggestion with detailed explanations since even small adjustments can result in the batter scoring more runs [13]. A model should classify his or her position accurately regardless of whether two poses are nearly identical but have a few subtle differences. Based on the position of the shoulders and pelvis concerning the wicket and batter, fast-bowling techniques in cricket can be classified into four types [14]. In high-speed bowling, the front foot is struck at an angle between the line connecting the wickets and shoulders. The main hip and shoulders point towards the batter, and the front, hips, and shoulders are open. A front is the lower half, and a batter's side is the upper half. The upper body is alternated between different positions.

Coaches' abilities to identify precise biomechanical features are limited by the fourth-half-open approach and 2D representations. Nevertheless, due to their inability to replicate three-dimensional movements, 2D virtual coaches can't analyze factors such as the release point and body location. In-person coaching is preferable because it allows for a more thorough inspection to provide feedback on tiny changes in bowling technique. A sports biomechanics model and 3D modeling technology can assist in capturing, quantifying, and analyzing human movement during games with increased accuracy and objectivity [15]. An extensive study has been conducted concerning the relationship between fast bowling technique and injury [16]. Innovative motion analysis instruments have provided accurate and reliable monitoring of 3D joint motion to assist sports screening and intervention tactics [17]. However, it is necessary to manually calculate the angle and location of the crucial body parts. Their performance in measuring angles was subpar, even though they used deep learning techniques such as multi-layer perceptrons (MLPs), recurrent neural networks (RNNs), and long-short-term memories (LSTMs) [18].

Pandey's study [19] focused on predicting player performance in cricket. They utilized ML classifiers such as Naïve Bayes, RF, multiclass Support Vector Machine (SVM), and Decision Trees (DT) to classify the number of runs scored by batsmen and the number of wickets taken by bowlers. The Random Forest classifier provided the highest accuracy for both tasks, demonstrating the model's robustness in handling complex player performance data.

Raman Kumar et al. [20] developed a model to predict cricket player performance using algorithms like Decision Tree, Random Forest, SVM, and Naïve Bayes. Using data from ESPNcricinfo, it focuses on batting and bowling performance, applying sophisticated data preprocessing and attribute scaling to enhance accuracy. The study aims to improve the precision of player performance evaluations, contributing valuable insights for talent discovery and sports analytics

Vistro et. al. [21] employed a data analytics methodology, combining many data sets and sophisticated algorithms to get precise predictions of match outcomes. This study highlighted the significance of player statistics, match conditions, and historical data in constructing predictive models, demonstrating the efficacy of machine learning in strategic planning and decision-making in the sport of cricket.

Awan et al. [22] investigates the utilization of big data analytics and machine learning to predict cricket match outcomes. The authors employed linear regression models implemented in the Spark ML framework to predict team scores, yielding a significant level of accuracy and minimum error rates. The study demonstrates the potential of big data approaches to improve predictions and analysis in cricket, with the potential to expand these applications to other sports.

Computer vision has also been applied to cricket to automate various aspects of the game. Shahjalal et al. [23] proposed an approach to automate the scorecard in cricket using computer vision and ML. Their method involved using a Haar-cascade classifier for region selection and logistic regression for gesture recognition, significantly reducing manual effort in updating scorecards and improving the game's flow.

Kaythry et al. [24] developed a computer vision-based system that enables real-time 3D hand gesture identification for playing hand cricket. The system utilizes a CNN to recognize hand motions corresponding to numbers 1–6. This enables users to engage in a simulated hand cricket game versus a computer.

Siddiqui et al. [25] explores predicting cricket strokes using computer vision and machine learning. The method achieves high accuracy by analyzing video features of eight stroke types with MediaPipe and employing algorithms like RF, SVM, and LSTM. This technique offers significant improvements for coaching and player performance analysis.

Posture estimation is crucial in sports like cricket as it helps determine a player's biomechanics and identifies areas for improvement [10]. Cricket requires the bowler to maintain a good posture during the delivery stride in order to deliver the ball accurately, quickly, and efficiently. Position estimation techniques can be used by athletes and coaches to identify weaknesses in their technique, and custom training regimens can be developed to enhance their performance. Several studies have examined posture analysis in sports, including cricket, and found that posture estimates can improve player performance [12,26]. It is possible for poor posture to negatively affect the performance of a cricket bowler in several ways. An incorrect posture can affect a player's ability to pitch accurately, speed a ball, and deliver a delivery stride efficiently, leading to injuries. The bowler's posture ultimately influences the ball's trajectory and speed and how energy is transferred from the bowler to the ball. Researchers found that bowlers with strong postures produced more accurate and faster balls than weak ones [27,28].

In the studies [28,29], the focus was on putting cricket strokes into groups. The researchers also looked at how to track players' and teams' movements during practice, games, warm-ups, and competitions, especially in volleyball, basketball, soccer, and tennis. The Human Action Recognition (HAR) research program focuses on public datasets and everyday actions. A few researchers have referred to the work presented in [29] about computer vision, machine learning, and deep learning applications in sports, supporting the strong literature in this field. The use of computer vision models and techniques has become increasingly significant in the domain of sports. The implementation of novel technologies has effectively tackled certain obstacles athletes encounter, particularly in response to the growing prevalence of unethical behaviors such as cheating and doping. Through the utilization of computer vision, diverse applications have been created to mitigate the burden on athletes and augment the overall credibility of the game. Computer vision systems use cameras to accurately detect no-balls, thus reducing the occurrence of erroneous dismissals and promoting fairness in the outcome. Furthermore, the use of these sophisticated methodologies facilitates the enhancement of overall gaming proficiency, resulting in a more captivating and gratifying encounter for both participants and spectators [30].

In line with the progress made in computer vision for sports [31], this study presents a brand-new model made just for recognizing cricket strokes. The model aims to identify and group the most important cricket strokes, like the block, cut, drive, and glance. Using different visual cues like the batter's head, feet, bat, and hands, the model correctly identifies and sorts each stroke. This new way of doing things helps analyze cricket players' overall performance and makes the game easier for both players and fans to understand and enjoy.

Materials and methods

This section explores the mechanics of the bowler's bowling motion and the potential injuries that can occur during cricket bowling. It also examines computer vision systems that analyze and assess bowling posture and motion.

Bowling action in cricket

Bowling in cricket involves tossing the ball toward the batter's wicket. Both bowlers and all-rounders have exceptional batting and bowling abilities. In contrast to throwing, bowling leaves less room for the elbow to extend fully. In addition to presenting the ball to the batting team, delivery can also refer to the act of presenting the ball to the bowler. In cricket bowling, the concept of symmetry in movements refers to the balanced and coordinated motion of both sides of the bowler's body. Symmetric movements can lead to more efficient and accurate bowling for several reasons:

1. **Balance and Stability:** Symmetrical movements ensure the bowler's body is well-balanced during the delivery stride. This balance is crucial for maintaining stability and precision when targeting the wickets.
2. **Energy Transfer:** Efficient energy transfer is key to effective bowling. Symmetry in the bowler's actions allows for a smooth, coordinated transfer of energy from the run-up through the delivery, enhancing the power and speed of the ball.
3. **Consistency:** Symmetrical movements contribute to a consistent bowling action. Consistency is vital for accuracy and predictability in bowling, enabling bowlers to deliver the ball in a desired manner repeatedly.

On the other hand, asymmetry in bowling movements – where there is an imbalance or lack of coordination between the two sides of the body – can lead to several issues:

1. **Inconsistencies in Performance:** Asymmetrical movements can result in inconsistencies in ball delivery, affecting the bowler's accuracy and control. This unpredictability can hinder performance, making it difficult to achieve desired outcomes.
2. **Increased Injury Risk:** Asymmetry often leads to undue stress on certain body parts, as the imbalance forces some muscles or joints to compensate for others. This can increase the risk of injuries, particularly in high-stress areas like the shoulder, elbow, and knee.
3. **Reduced Efficiency:** Asymmetric movements can reduce the efficiency of the bowling action. This inefficiency may manifest as reduced speed or power in the delivery, potentially diminishing the bowler's effectiveness. Understanding and correcting asymmetries, therefore, is crucial for enhancing performance and reducing injury risks in cricket bowling.

A game has six "overs" or sets of six deliveries. Team members quickly follow each other after the first bowler finishes his/her over. Cricket rules outlined specific rules that describe the correct technique for bowling a ball [31]. A bowled ball that violates the rules will be signaled "no ball" by the umpire. If the batsman can hit the wide ball with a cricket bat, it won't be called wide. A bowler who relies solely on speed can throw off the batter's timing, while another who uses flight and spin can do the same. A spin bowler's ball travels further and strikes the pitch obliquely instead of a fast bowlers.

There are several types of bowlers, from fast bowlers who rely on speed as their primary weapon to swing and seam bowlers who use flight and spin and slow bowlers who use spin and flight. A bowling motion is a series of actions, as shown in Fig. 1, designed to place the ball within striking distance of the batsman.

A bowler's balance, fitness, and technique are integral to the game. These principles are commonly found in instruction manuals that guide bowlers to improve their skills. By prioritizing balance, maintaining physical fitness, and honing their technique, bowlers can lay the groundwork for success in the game [8]. In contrast, good coaches recognize that many successful bowlers employ unique styles and develop new, improved techniques. Instruction manuals describe some of the most commonly taught techniques. The bowler's approach refers to his or her motion before releasing the ball into the air. The term "run-up" may also be used. A spinner's approach doesn't change as the pace of the bowler changes from fast to medium. Every bowler needs to consider some critical factors [32].

1. *Posture Balancing*: An imbalanced posture will result in an incorrect outcome.
2. *Consistency throughout the game*: The bowling action should be consistent throughout the game.

   Maintaining good body and head posture when bowling in cricket is also crucial. To achieve a balanced movement that leads to the desired outcome, it is important to have a smooth flow of movement between each step. Fast and medium-pacer bowlers approach the game straightforwardly and aim directly at the target. On the other hand, spin bowlers employ a wider range of techniques [33–35]. The following are other aspects to consider when choosing a strategy:

   a. A shorter stride is used to ease into the bound, which is then gradually lengthened.
   b. Running toe-to-toe with a slight forward lean.
   c. Keeping hands close to the body while jogging and making repetitive pumping motions. The tucked-in run-up sets the precedent for the subsequent delivery by confining all movements within a narrow pathway and progressing toward the intended target. Bowlers frequently utilize their non-bowling hands to obscure the ball and hide their grip on the bowling ball.
   d. Taking the time necessary to reach the desired cruise speed and arrive at the bound is sufficient. Some bowlers, particularly those who bowl with their chests, tend to run through the crease.

Injury - mechanics behind cricket bowling action

In numerous studies, quick bowling has been linked to back problems. There are three basic approaches to fast bowling: side-on, front-on, and mixed. According to research [36–38], mixed bowling action is associated with a higher risk of injury. A reduction in injury risk can be achieved by avoiding or reducing movements such as counter rotation of the shoulders. Due to the angle of the trunk with the bowling arm, injuries are more likely to occur when bowling [39,40]. Combining these three factors puts the lumbar vertebrae under strain, resulting in damage. Several studies have shown that the angle of the bowler's leg can cause damage to the lumbar spine [12,41–43]. A fast bowler with a stretched front knee position is likelier to suffer an injury than a flexed knee position. To better understand the mechanisms behind lumbar spine injuries, it is important to examine movement variability across multiple trials in lumbar spine injuries. Several hypotheses have been proposed to explain why low back injuries are associated with a lack of diversity. If an athlete's motor habits are rigid and inflexible, they can perform an activity at a lower complexity. Therefore, less movement variability may increase the risk of overuse injuries since repeated stresses on the same tissue are concentrated with less time between them. There has been a link between this method of training and the overuse of injuries [15,44].

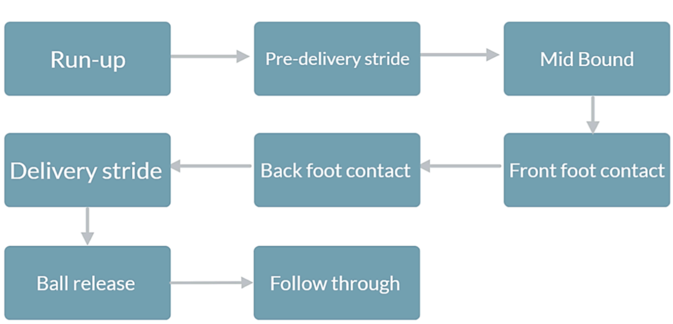

Fig. 1. Bowling action series in Cricket.

Computer vision - deep learning frameworks for bowling action- posture prediction: a 3D pose estimation

Computer vision is a subfield of AI that trains computers to analyze images in a manner similar to humans. One of the most common applications of computer vision is pose estimation. The initial joint angles influence bowling mechanics [44] as shown in Fig. 2.

This section aims to provide an overview of the steps involved in pose estimation using deep learning. Pose estimation is a crucial computer vision component and holds great promise for future applications. Human pose analysis and tracking involve identifying and tracking semantic critical points associated with the human body. Monitoring and analyzing human poses require identifying and following semantic key points in computer vision. Detecting semantic key points in real-time video requires significant computation power. In recent years, technological advancements that necessitate real-time processing have opened up new applications, such as autonomous vehicles and robots that transport packages [45,46].

CNN is the basis of some of the most advanced image-processing models available today. Consequently, cutting-edge approaches often employ CNN architectures that are designed explicitly for inferring human postures [47]. These methods can be divided into two categories:

i. Bottom-up methods

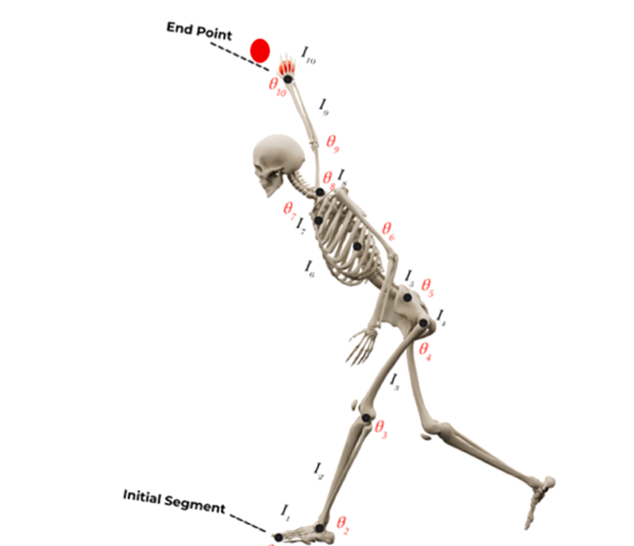

Fig. 2. A 3D model of a mechanical joints' representation of a bowling action.

ii. Top-down methods

Bottom-up approaches assess each joint individually before aggregated data is used to create a single posture. The bottom-up approach is preceded by deep cuts. A top-down approach, on the other hand, begins by running a person detector and estimating body joint positions within the bounding boxes. It is impossible to reliably estimate someone's pose using the usual object detection methods since people are not perceived as anything other than a box (a square) [48]. Performing stance recognition and position monitoring tasks can help machines learn about human body language. Furthermore, conventional stance-tracking methods do not work well because they are neither fast nor resistant to impediments. Real-time stance detection and tracking with high performance will significantly advance computer vision. Human stances can be tracked by computers in real time to gain a deeper understanding of human behavior [49,50]. The 3D Human Pose Estimation technique analyzes images and videos to estimate the position of joints in 3D space. This topic has received much attention recently due to its ability to provide 3D structure information on the human body. This technology can be used for 3D animation, virtual reality, and 3D action prediction. It is possible to predict 3D human positions from a monocular photo or video (typical camera feeds) [51–53].

This study focuses on the role of bowlers in executing deceptive movements, specifically analyzing the biomechanics of bowling techniques. A case study approach is adopted, centering on Umran Malik's performances during IPL 2022 and 2023. By examining both his successful and less effective deliveries, we aim to uncover patterns and biomechanical variations that contribute to deceptive movements in cricket.

Data collection, preprocessing and experimental design

This study utilized a dataset comprising 100 video sequences of professional cricket bowlers, specifically focusing on matches from the Indian Premier League (IPL) 2022 season. The videos, with an average duration of 10 s per clip, were recorded under consistent lighting and camera conditions during live matches. These videos were sourced from the official Star Sports broadcasts, ensuring high resolution and frame rates for accurate analysis. The experimental design involved extracting XYZ coordinates of body joints from these video sequences using the OpenPose AI engine. The extracted data was then labeled for training and testing the machine learning models (RF, KNN, and DT) to predict postural changes. The dataset was split into 80 % training and 20 % testing subsets, ensuring a robust evaluation of the model's performance.

Annotating deceptive movements requires domain expertise to identify biomechanical nuances accurately. To achieve scalable and accurate labeling, the following strategies were employed:

1. Engaging cricket analysts and coaches to annotate key movements.
2. Using collaborative platforms for crowdsourced annotations validated by experts.
3. Leveraging semi-automated annotation tools that combine manual input with AI-based suggestions.
4. This hybrid approach ensures both accuracy and scalability, catering to the complexity of deceptive movements.

The video data used in this study was sourced from publicly available platforms like IPL broadcasts and authorized archives, ensuring adherence to copyright regulations. To address ethical concerns, data was anonymized, focusing solely on biomechanical analysis without revealing player identities. For future research, partnerships with governing bodies and explicit permissions will be sought to ensure compliance. Additionally, safeguards such as encrypted storage and restricted access were implemented to prevent unauthorized usage [93].

Ethical considerations were given high priority in this study. The video data utilized was publicly available through official IPL broadcasts, ensuring no violation of data privacy. Additionally, no personally identifiable information (PII) of the players was used. The study adhered to ethical standards by anonymizing all data, focusing solely on biomechanical analysis without any implications on player identity. For future research involving private data, obtaining informed consent from players and organizations will be a fundamental prerequisite.

Pseudo code of the proposed system

Input: Athlete/Player Video File Upload to the System

Output: Postural Changes Prediction
1) Upload Videos to AI Engine (OpenPose)
2) Extract Frames and XYZ Information using CNN (VGG−19)
3) Store the XYZ Information in Real-Time Database
4) If all videos are uploaded:
Repeat the following steps for each video:
5) Extract Postural Information (XYZ Coordinates) using AI Engine
6) Label the Data with Postures using a Reference Video (Good Performance) and Other Videos (Not up to the Mark)
7) Segment the Data into Training and Testing Sets
8) Apply Classification Models (RF and KNN) to the Training Data
9) Predict Postural Changes using the Trained Models on the Testing Data
10) Output the Postural Changes Prediction
End If
11) End

Artificial intelligence: deep learning frameworks for cricket bowler pose estimation

Artificial intelligence can estimate human poses using three frameworks listed below:

OpenPose: One of the most popular approaches to estimating multiple people's poses is OpenPose. It is an open-source, multi-user, real-time pose detection system with high precision levels [54,55].

Simply - "OpenPose is a system that identifies and tracks key body points, like arms and legs, from images or videos."

DeepPose: DeepPose estimates human poses using a deep neural network. These layers are formed by a convolution layer that captures all hinges and joints and then a fully connected layer that captures all connections [56,57].

PoseNet: Based on Tensorflow.js, PostNet is a lightweight architecture that can be run on mobile devices and web browsers [58].

Fig. 3 shows the overall research flow. This study uses the OpenPose AI engine to analyze player bowling action. Deep learning algorithms are integrated into OpenPose to calculate postural changes [59,60]. Umran Malik's bowling performances during the Indian Premier League (IPL) - 2022 matches of Sunrisers Hyderabad from Star Sports were used as inputs for this research framework, as mentioned in the motivation section of this article.

Open pose-algorithmic architecture

With Open Pose, 135 key points on the human body, hand, facial expression, and foot can be detected in real-time [61,62]. Unity plugin has also been implemented in C++ and made available for the public as open source [63].

- In the first step, feature maps are extracted from the input image using a primary CNN network.
- Part Confidence Maps and Part Affinity Fields are generated from the feature map using a multistage CNN pipeline.
- In the final step, a greedy bipartite matching algorithm generates confidence maps and part affinity fields to determine the poses of each individual in the image.

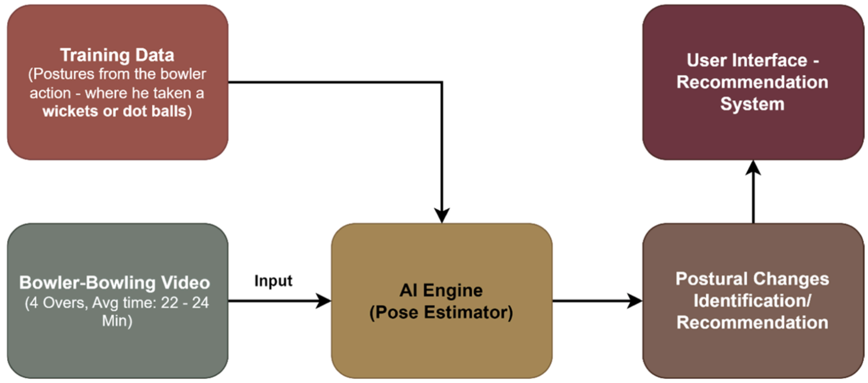

Fig. 3. Proposed framework for pose estimation from bowler action.

Confidence Maps: A confidence map is a 2D representation of the perception that a specific frame element may be placed in each pixel. The maps help determine where the body parts of a person are located [64].

Part Affinity Fields: Part Affinity fields encode limb positions and orientations of people in an image using 2D vector fields. Data is encoded as a pair of connected body parts [65].

Models based on Human Kinematics, also known as skeleton-based models, are used for 2D and 3D pose estimation. A flexible and intuitive human body model illustrating joint positions and limb orientations represents the structure of the human body. As a result, skeleton pose estimation models are used to capture the relationships between body parts. Kinematic models are limited in their ability to represent texture or shape information. Convolution, more specifically discrete convolution, is the concept of extracting key features from images while preserving the ordering of the information. A kernel is convolved with the input to produce the output. Neuronal networks in the human visual cortex produce a response analogous to this process.

An OpenPose 3D pose estimation algorithm provides output in X, Y, and Z coordinates and labels for body joints and parts. The proposed model framework model is shown in Fig. 4. It includes information about ankle movement, hip movement, and other changes to gait parameters. Through tracking key points on the body, such as ankles and hips, OpenPose captures the positional changes in three-dimensional space, allowing for the analysis and interpretation of gait parameters. It can be useful for understanding body movements, analyzing walking patterns, and assessing overall gait dynamics. A discrete convolution is an approach to extracting key features from images while preserving the information's order. A kernel is convolved with the input to produce an output. This process is analogous to that produced by neural networks in the human visual cortex [66,67].

Results and discussions

This section discusses Artificial Intelligence-based Deep Learning frameworks for estimating cricket bowler poses based on Open-Pose architecture.

Video clips collection for extraction of datasets

The bowling video clips that Umran Malik used during IPL 2022 and IPL 2023 were recorded from web platforms like Hotstar and Jio Cinema, respectively. Umran Malik's best and worst bowling performances from the 2022 and 2023 IPL matches have been analyzed based on a statistical analysis of both series [68–70]. Figs. 5 and 6 show Umran Malik's performance statistics. The data was collected from the IPL Official Website (www.iplt20.com).

X-axis labels mentioned in Figs. 5 and 6 are given in Table 1.

Fig. 7 shows the comparison of Umran Malik's complete bowling performance stats from IPL 2022 and IPL 2023. According to the exploratory data analysis, his performance in IPL 2023 hasn't been as good as IPL 2022.

In this case, considered his best and bad bowling figures – In terms of

i. Number of Runs given,
ii. Number of Wickets taken,
iii. Number of Dot balls.

In this scenario, we are considering the 2022 IPL - T20 match between Sunrisers Hyderabad (SRH) and Gujarat Titans (GT). During this match, he took 5 wickets from 4 overs and conceded 25 runs. His best performance in IPL 2022 came in this match, but unfortunately, in his next two matches, his performance was drastically different, and he had poor performances. Those matches were against Delhi Capitals (DC) and his performance has been reported in Table 2 and Table 3.

As a result of this analysis, we have focused on these three matches

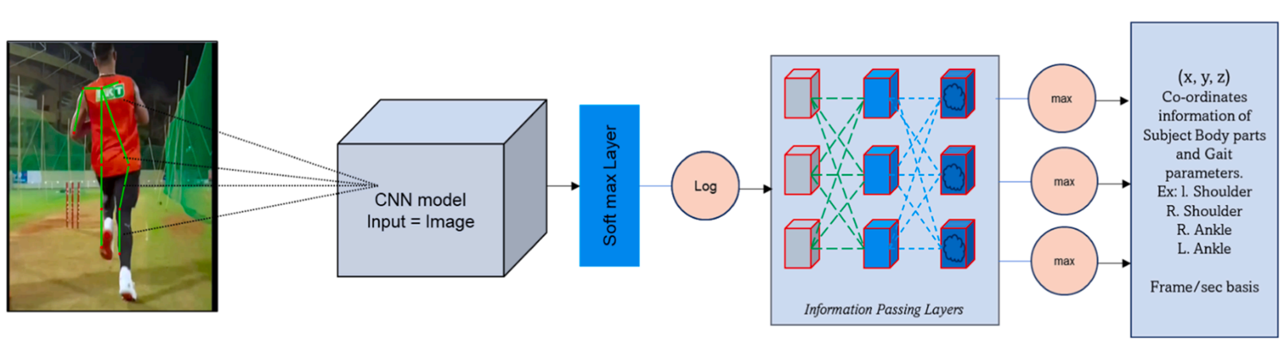

Fig. 4. Sample Pose Estimation model on Umran Malik bowling action using CNN.

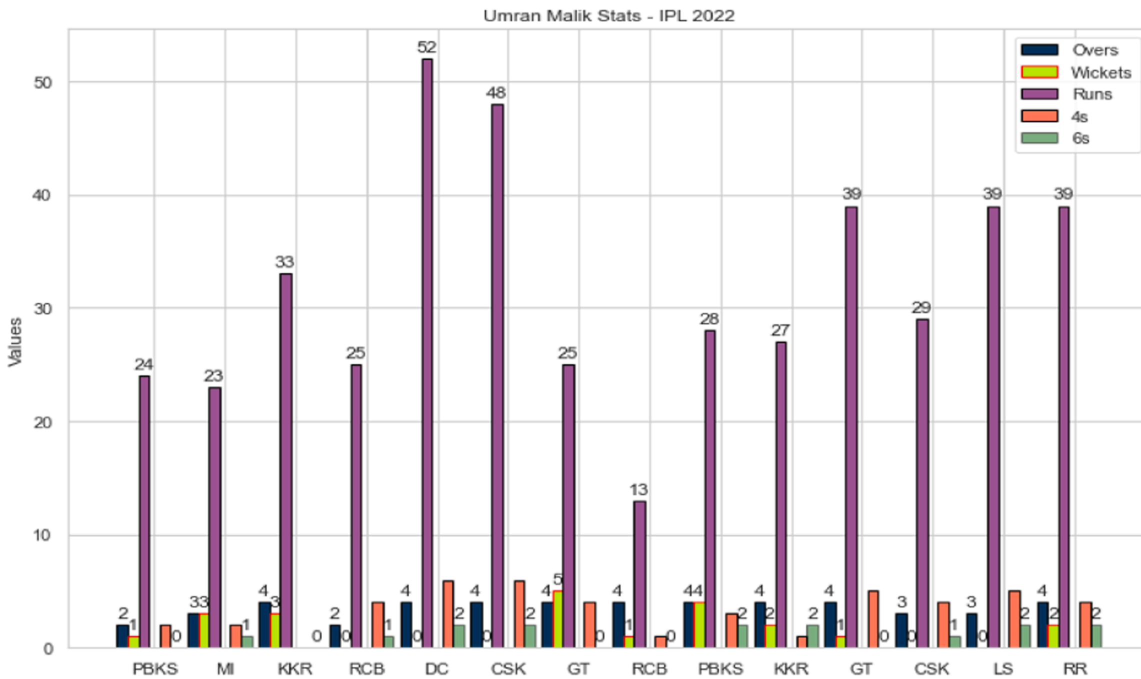

Fig. 5. Umran Malik 2022 IPL Performance.

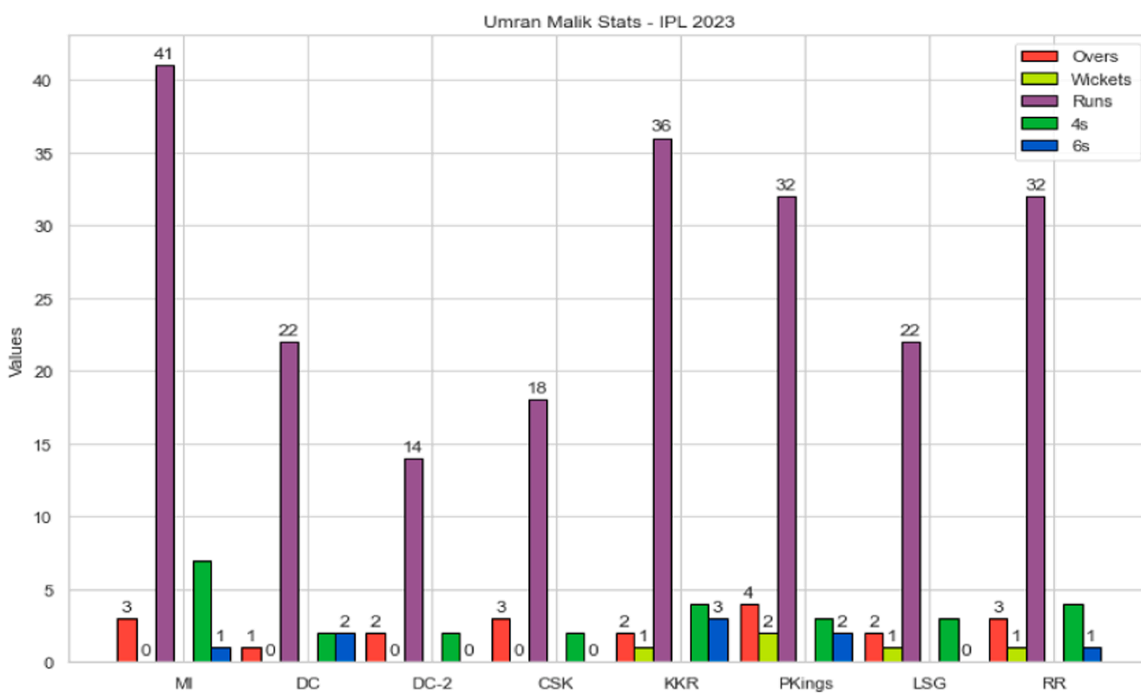

Fig. 6. Umran Malik 2023 IPL Performance.

and analyzed Umran Malik's bowling videos - based on the selected scenarios.

i. Wicket-taken bowling clips (Total 5 Video clips)
ii. Boundaries (4 - runs) conceded bowling clips (Total 16 Video clips)
iii. Sixers (6 - runs) conceded– bowling clips (Total 4 Video clips)
iv. When dot ball bowled - bowling clips (Total Video 29 clips)

We collected 54 video clips as primary data for the pose estimation process. In this case, 54 bowling deliveries were considered, on an average of nine overs, where the average video clip duration was 56–60 min. This video quality is often called 720p since it has a resolution of 1280 × 720 pixels.

This study used 30 fps (frames per second) as a common standard for smooth playback.

So, 60 min of video clips at 30 fps has:

*60 min *60 s/min **30 frames/second =*108,000 frames On nine body elements, XYZ coordinates data extracted total of*

*108,000 frames *9 body parts *3 sub-columns* = ***2916,000*** *datapoints*

Table 1
IPL Cricket Team Label with names.

S.No	Team Code	Team Name
1	CSK	Chennai Super Kings
2	DC	Delhi Capitals
3	GT	Gujrat Titans
4	KKR	Kolkata Knight Riders
5	LSG	Lucknow Super Giants
6	MI	Mumbai Indians
7	RCB	Royal Challengers Bangalore
8	SRH	Sunrisers Hyderabad
9	RR	Rajasthan Royals
10	PBKS	Punjab Kings

information gathered.

The Open Pose estimation algorithm generates annotations on the video and extracts 3D coordinates in XYZ dimensions using OpenCV. This information represents actual 3D coordinates in meters of changes on the body parts—gait parametric changes. This information was saved in the.csv file.

Visibility: Visibility is defined in the corresponding pose landmarks.

Segmentation Mask: The output segmentation mask predicts when enable segmentation is set to true. Masks have the same width and height as input images. There are values in the range of [0.0, 1.0], with 1.0 indicating a high degree of certainty that a pixel is "human" and 0.0 indicating a "background" pixel [71,72].

Based on the timeline – manually mark the labels on to the x, y, and z information (Postural changes) Classes are -

- C1: Wicket-taken bowling clips
- C2: Boundaries – 4 runs conceded bowling clips.
- C3: Sixers – 6 runs conceded bowling clips.
- C4: Dot ball bowled - bowling clips.

Here, the research breakthrough was found using machine learning methods to find the bowler's postural changes during his best and worst performances. The dataset was divided into training and testing phases. Training consists of best-performance samples of Classes C1 and C4, whereas the testing dataset consists of bad–performance samples of Classes C2 and C3.

Machine learning algorithms on postural prediction

In RF, a large number of decision trees are generated during training, which are then aggregated to obtain the final output. As a result of grouping decision trees into RFs, their overall performance and accuracy are enhanced. Bagging, also known as bootstrap aggregation, involves randomly selecting samples from the training dataset, allowing for multiple selections of the same sample. A binary partitioning method is used to select a subset of input features for each tree node [73]. The Gini Index determines the split point, aiming for a lower value that indicates a better separation of classes. Minimizing the Gini Index improves the quality of the splits in decision trees.

Unlike traditional classifiers, KNN directly uses the memory of training examples without fitting a model. However, conventional KNN has limitations, including high computational complexity and uniform treatment of all nearby specimens. To address these issues, KNN can employ graph distance metrics to efficiently identify closest neighbors and improve classification accuracy. When trained and tested on data, KNN, along with DT, RF, Bagging, and ExtraTree Classifier algorithms, achieved a 70.1 % accuracy in detecting postural changes across classes C1, C4, C2, and C3.

Here are the algorithm's accuracy comparisons, shown in Fig. 8.

Performance measures

There are four performance parameters for estimating algorithm performance: accuracy, precision, recall, and F1 Score. Accuracy, pre-

Table 2
Umran Malik's best bowling performance in IPL 2022.

SRH Vs GT 27/04/ 2022	**Overs**	**Maiden**	**Runs**	**Wickets**	**Econ**
	4	0	25	5	6.25
	0-Dotball	**4 Runs**	**6 Runs**	**Wide's**	**No-Balls**
	12	4	0	0	0

Table 3
Umran Malik's underwhelming performance in IPL 2022.

SRH Vs CSK 01/05/ 2022	**Overs**	**Maiden**	**Runs**	**Wickets**	**Econ**
	4	0	48	0	12
	0-Dotball	**4 Runs**	**6 Runs**	**Wides**	**No-Balls**
	8	6	2	1	0
SRH Vs DC 05/05/ 2022	**Overs**	**Maiden**	**Runs**	**Wickets**	**Econ**
	4	0	52	0	13
	0-Dotball	**4 Runs**	**6 Runs**	**Wides**	**No-Balls**
	9	6	2	2	0

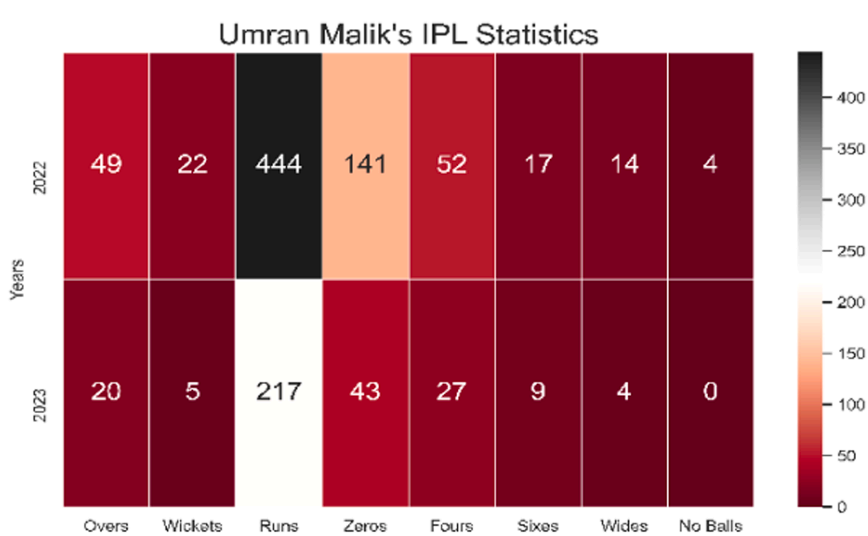

Fig. 7. Umran Malik 2023 IPL Performance.

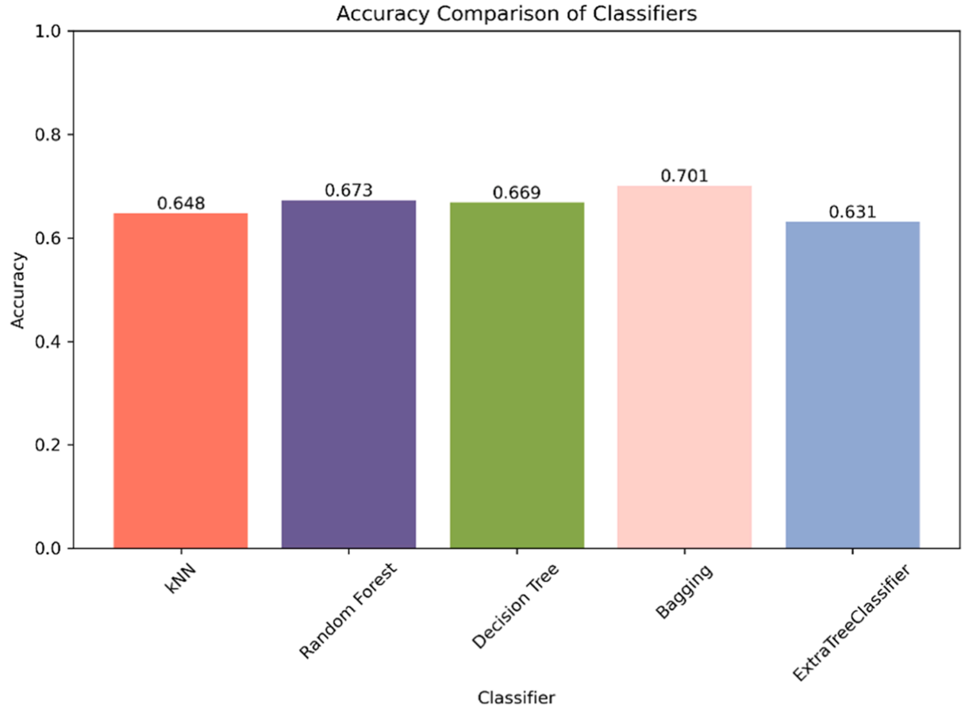

Fig. 8. Algorithms accuracy comparison.

cision, recall, and F1 score are commonly selected performance parameters because they provide valuable insights into algorithmic performance [74–76]. These parameters depend on the four conditions: True Positive – TP, False Positive – FP, True Negative – TN, and False Negative – FN.

- **Accuracy:** Accuracy measures the overall correctness of an algorithm's predictions by calculating the proportion of instances classified correctly relative to the total number of instances. It is commonly used to evaluate the effectiveness of algorithms. Mathematically, accuracy is the ratio of true predicted values to the total predicted values, as shown in Eq. 1.

$$Accuracy(Acc) = \frac{(TP + TN)}{(TP + TN + FP + FN)} \times 100 \tag{1}$$

- **Precision:** Precision measures how accurate an algorithm is at identifying positive instances. It compares the proportion of correct positive predictions to the total number of positive predictions, including both true and false positives. Precision assesses the algorithm's ability to predict positive instances accurately, excluding false positives. For class 1, precision is the ratio of actual class 1 members among all instances predicted as class 1, as shown in Eq. 2.

$$Precision(Pre) = \frac{TP}{(TP + FP)} \times 100 \tag{2}$$

- **Recall:** Recall, also known as sensitivity or true positive rate, measures an algorithm's efficiency in detecting all positive instances. It is computed as the proportion of correct positive predictions to the total number of positive occurrences, including both true and false negatives. Recall evaluates how well the algorithm minimizes false negatives. For class 1, recall is the ratio of actual class 1 values correctly predicted as class 1, as shown in Eq. 3.

$$Recall(Rec) = \frac{TP}{(TP + FN)} \times 100 \tag{3}$$

- **F1-Score:** In statistics, F1 measures precision and recall, which are calculated as the harmonic mean. The approach provides a well-proportioned evaluation by considering both precision and recall simultaneously. F1 scores can be useful for determining whether the number of positive versus negative instances within a dataset is unequal. Combining precision and recall aids in assessing the algorithm's overall performance comprehensively, as shown in Eq. 4.

$$F1 - Score(F1S) = \frac{2 * (Precision \times Recall)}{(Precision + Recall)} \tag{4}$$

Fig. 9 shows the algorithm learning curves and performance metrics. The standard precision-recall curve graphs illustrated in Fig. 10 provides additional insight into the efficacy of the postural change detection model and understanding of performance metrics. Using learning curves, the efficacy of a model is depicted graphically during training and testing. In most cases, these curves represent model performance metrics, such as accuracy or error rate, as a function of the number of training iterations or the size of the training dataset. It's possible to understand better how a model's efficacy progresses over time by analyzing its learning curves. Learning curve convergence indicates whether a model is at a consistent level of performance or whether additional training iterations are required. As a result of using learning curves, prospective concerns can be detected, such as overfitting, which occurs when a model exhibits satisfactory performance on training data but poor performance on novel, unobserved data. It is also possible to identify underfitting through learning curves, which occurs when the model cannot capture the fundamental patterns in the data. Model training and optimization can be improved through this understanding, facilitating informed decision-making by researchers and practitioners.

In contrast, conventional precision-recall curve plots comprehensively evaluate the balance between precision and recall for detecting postural changes. Precision and recall are important metrics to evaluate a classification model's performance. A precision measure is the ratio of true positives (i.e., correctly observed postural changes) to the total number of positives. Alternatively, recall measures the ratio of true positive instances to the total number of actual positive instances.

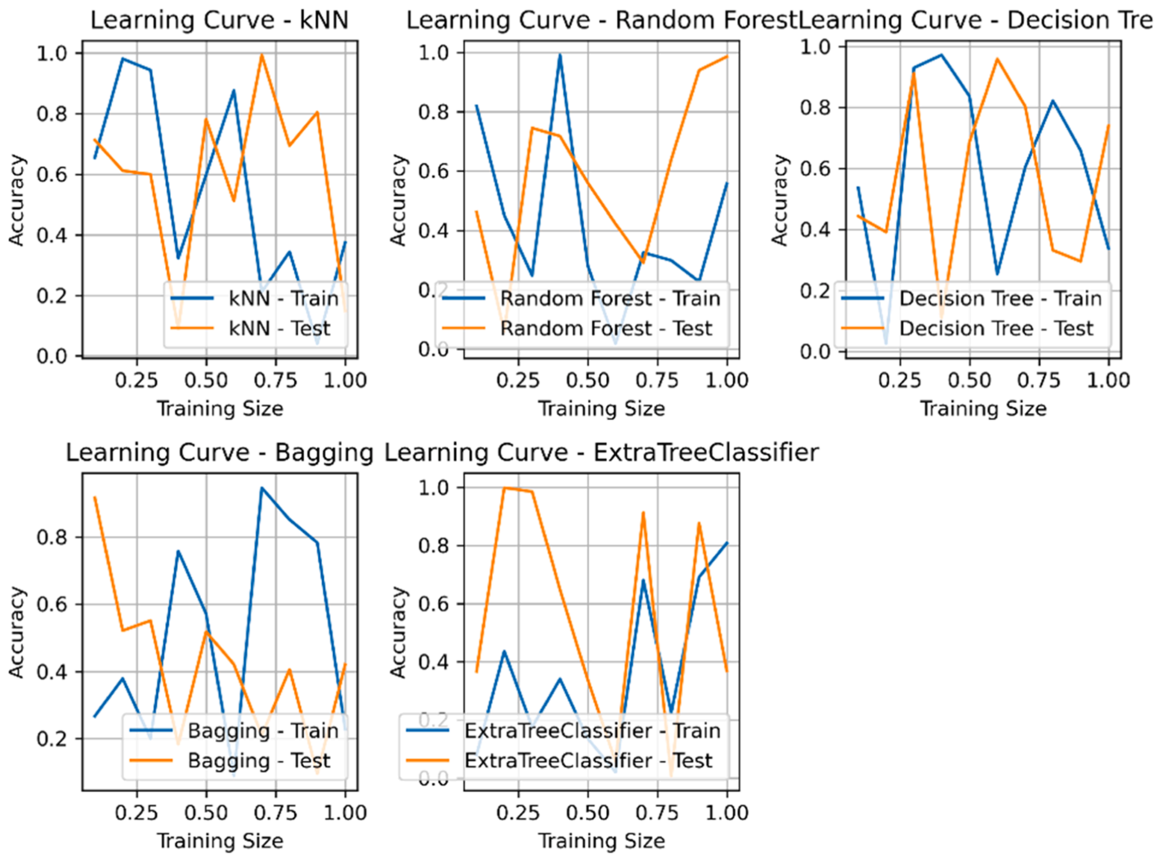

Fig. 9. Performance characteristics of ML algorithms.

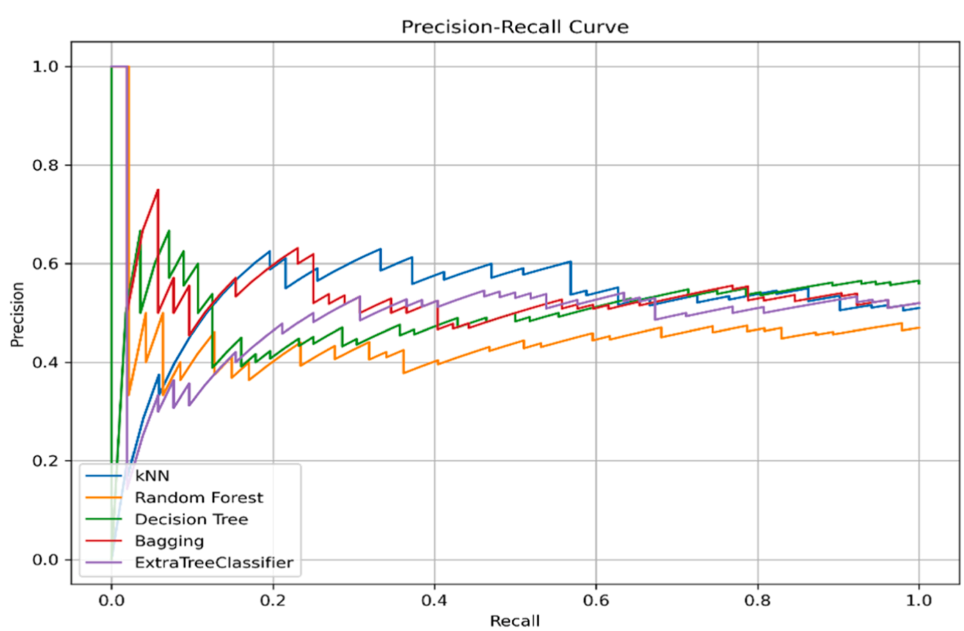

Fig. 10. Precision-Recall curves of different machine learning algorithms.

Precision-recall curves show how precision and recall metrics fluctuate as classification thresholds change. We can use this curve to determine the ideal threshold that achieves a balance between precision and recall tailored to the application. Due to the potential consequences of false positives and false negatives, it is important to account for them when detecting postural changes. Learning curves and precision-recall curve graphs provide a comprehensive understanding of the model's performance in detecting postural changes. They assist in identifying potential issues during training, optimize model parameters, and enable informed decisions regarding classification thresholds. In addition to enhancing the precision and dependability of the model, the observations will also direct future research initiatives in the domain of posture identification in cricket and other sports.

This study focuses on developing an advanced posture recognition model for cricket players using computer vision techniques, particularly on predicting perceived future actions based on recorded video input. This skill, which is challenging for humans to achieve with high accuracy, is crucial for performance assessment and virtual assistive coaching. The model demonstrates an impressive prediction accuracy rate of 60–70 % for postural adjustments. Integrating this innovative model enhances posture correction and serves as a valuable virtual coach. However, it is important to recognize that bowling outcomes, such as conceding runs and taking wickets, are influenced by additional factors, including the playing environment, pitch conditions, bowler mindset, and the characteristics of the opposing batsman.

By integrating computer vision technology into sports, particularly cricket, we can evaluate players' performance based on their body positioning within the game. A player's posture is analyzed to gauge their overall performance in this interdisciplinary fusion of technology and athletics. As a result, computer vision technology allows comprehensive evaluation of performance levels by considering the intricate relationship between posture and performance. A posture recognition model based on OpenCV-computer vision techniques was developed as a first step in the research process. Using this model, cricket players were able to predict changes in posture alignment based on extensive testing accurately [77]. The focus on postural imbalance as a key performance determinant is indeed valid, but it is essential to recognize that other contributing factors, such as the player's mental and physical conditions, environmental aspects, and ground or pitch conditions, play equally critical roles in overall performance. This research should be expanded to encompass various levels of analysis to enrich the breadth of understanding. Integrating players' and athletes' mental and physical health conditions, ground conditions, internal and external pressures, and practice levels is essential to achieving a holistic performance evaluation. The inclusion of these multifaceted factors into the research design will undoubtedly result in a more comprehensive and insightful analysis [78].

This study presents a promising methodology within the realm of sports analysis and virtual assistive coaching.

Despite this, it's necessary to acknowledge and thoroughly address the inherent limitations of this research.

- A notable limitation of the study is its focus on Umran Malik. Therefore, whether the results obtained can be generalized to other cricket players and bowlers with distinct styles and techniques remains uncertain. As a result, it becomes crucial to assess the applicability and generalizability of the model across a wide spectrum of bowlers.
- Additionally, the study's reliance on Umran Malik's bowling clips and OpenCV and Pose estimation algorithms underscores the importance of data quality and availability. The quality and accessibility of these data points may impact the precision and reliability of the results. A comprehensive compilation of high-quality bowling footage from a wide range of bowlers presents inherent challenges and requires substantial resources.
- A restricted set of evaluation metrics, such as accuracy, precision, recall, and F1 score [11,79,80], are used to evaluate the efficacy of machine learning models, specifically machine learning algorithms like KNN, RF, DT, Bagging, and Extra Tree Classifier. In addition to providing valuable insights into the model's performance, these metrics may not adequately capture all relevant aspects needed to evaluate the virtual assistant's effectiveness. To provide a more holistic appraisal, supplementary metrics about practical feasibility and tangible real-world outcomes, like analyzing coach-player interaction dynamics or observing performance improvements, would be added to the evaluation framework.
- This study focuses on pre-recorded bowling footage, excluding discussions of real-time analysis during live cricket matches. Real-time analysis brings additional complexity, requiring prompt processing and decision-making within constrained timeframes. Virtual assistive coaches must incorporate real-time analysis functionalities to be practical when deployed in live matches.

The results of this study, with a prediction accuracy of 60–70 %, demonstrate the potential of AI-driven pose estimation in enhancing cricket training regimens. By analyzing postural changes, the proposed model offers valuable insights for coaches and players to identify areas of improvement. For instance, understanding postural imbalances can help reduce injury risks by adjusting training intensity or refining techniques. Additionally, integrating this model into a virtual coaching platform can provide personalized feedback and recommendations, making it a practical tool for players at all skill levels. Beyond cricket, this approach can be extended to other sports to enhance performance and minimize injuries through biomechanical analysis.

Comparative analysis with similar studies

To contextualize the findings, a comparative analysis was conducted with existing pose estimation and motion prediction studies. Similar studies in sports have utilized various machine learning and computer vision techniques to analyze athlete performance, with varying degrees of success. For instance, [91–94] highlighted the application of AI-based load balancing in software-defined networks (SDN), achieving an average accuracy of 65 %, which serves as a benchmark for comparable AI applications in classification tasks. Similarly, [95–97] reviewed OpenPose applications in sports, reporting accuracies ranging from 50 % to 68 %, depending on input data quality and model complexity. These benchmarks validate the robustness of our model, which achieved up to 70 % accuracy in predicting postural changes during bowling.

[98–100] explored 3D pose estimation for sports training in football, achieving a precision rate of 66 %, underscoring the effectiveness of deep learning frameworks like CNNs in motion analysis. Similarly, [100–102] applied real-time player tracking and pose estimation in basketball, demonstrating that such models are instrumental in performance assessment but face challenges in real-time application, particularly in team-based scenarios.

In cricket-specific studies, [103,104] developed AI-driven video analysis tools for performance evaluation, achieving accuracy metrics similar to our results. [105] focused on multi-person pose estimation in real-time sports scenarios using OpenPose, achieving a comparable accuracy range. These findings support the feasibility of using pose estimation frameworks for cricket, particularly in scenarios requiring detailed biomechanical analysis.

[106] conducted predictive modeling for athletic movements in cricket, using 3D pose estimation techniques that achieved moderate accuracy. Our results, with a higher accuracy range, indicate that focusing on specific movements like bowling can yield more precise results. Additionally, [107] utilized pose estimation to derive performance metrics in cricket, emphasizing its potential for training regimens. [108,109] extended this by applying machine learning for bowling analysis, achieving insights into postural changes similar to those in our study. These comparative studies underline the unique contributions of this work, particularly in achieving higher accuracy in a domain-specific application, highlighting its practical implications for cricket training and virtual coaching. Moreover, they suggest the potential to expand the model's applicability to other sports disciplines, further advancing AI-based sports analytics.

Implications and challenges

While this study demonstrates the potential of AI to revolutionize cricket training, it is crucial to consider several broader challenges associated with implementing such technologies in sports environments:

1. Data Quality and Availability:

The accuracy and reliability of AI models heavily depend on the quality of input data. Inconsistent video resolutions, variations in lighting conditions, and occlusions in player movements can significantly affect the performance of pose estimation algorithms. Future research must explore advanced preprocessing techniques to standardize data quality across diverse scenarios.

Preprocessing cricket videos poses several challenges:

1. Occlusions: Players' movements are occasionally obscured by other objects or players. Image reconstruction techniques and multi-angle video feeds mitigate this issue.
2. Camera Angles: Variations in perspectives can lead to inconsistencies in pose estimation. Standardizing datasets to include a range of angles and calibrating models for these variations address this problem.
3. Resolution Differences: Video resolution inconsistencies impact frame quality. Techniques like super-resolution algorithms enhance low-quality frames for better analysis.

2. Variability in Player Performance:
   Athletic performance is influenced by numerous dynamic factors, including fatigue, mental state, and environmental conditions. These variables introduce unpredictability, which AI models must account for to provide actionable insights. Developing models that can adapt to real-time changes in player performance remains a key challenge.
3. Integration into Training Environments:
   Integrating AI systems into traditional training routines requires careful consideration of usability and scalability. Coaches and athletes may need training to understand and effectively utilize AI-generated insights. Additionally, AI systems must be designed to seamlessly integrate into existing workflows, ensuring they complement rather than disrupt training methodologies.
4. Ethical and Privacy Considerations:

The use of AI in sports raises ethical questions about player privacy and data ownership. Transparent policies must be established to ensure that data collection and analysis respect players' rights and are used solely for performance enhancement. The use of AI in professional sports has raised concerns about fairness and intrusiveness. While AI-driven tools can enhance performance and strategy, transparency is critical to ensure trust among stakeholders. Collaboration with players, coaches, and governing bodies can establish ethical guidelines, ensuring the technology supports fairness and complements human expertise rather than replacing it.

Also, to prevent misuse of the system for gambling or exploitation, these are the measures to ensure:

1. Controlled Access: Restrict system access to authorized personnel only.
2. Regulatory Oversight: Collaborate with governing bodies to monitor system usage.
3. Usage Tracking: Implement logging mechanisms to trace actions and ensure accountability.

These safeguards ensure the technology remains focused on its intended purpose improving athletic performance and training.

5. Broader Implications:
   AI systems like OpenPose and CNNs are poised to revolutionize sports training by providing precise feedback on athlete performance. However, challenges such as variability in player performance, data quality issues, and the integration of these systems into traditional training environments must be addressed.
6. Future Directions:

Future studies should focus on expanding the application to other sports and incorporating real-time analysis capabilities. Additionally, evaluating factors like player fatigue, energy levels, and mental resilience would provide a holistic perspective on athletic performance.

Conclusion

This study, focusing on predicting the next deceptive human movement based on video sequence analysis, with the application of a Cricket sports game, demonstrates the pivotal role of AI in enhancing athletic training and analysis. Utilizing advanced AI techniques such as OpenPose for pose estimation and CNN (VGG-19) for feature extraction, we successfully captured and analyzed the intricate movements of professional cricket players. The integration of classification models like RF and KNN enabled us to predict posture shifts with an accuracy of 63–70 %.

Although these results are relatively lower than the state-of-the-art, it is crucial to consider the complexity of analyzing the symmetry and asymmetry of cricket bowlers' techniques during delivery strides and predicting the next deceptive movement. The nuanced variations in these techniques present a challenging task for predictive modeling, which likely contributes to the observed accuracy levels. Despite this, our findings underscore the significant role of these biomechanical aspects in optimizing performance and preventing injuries.

Although this study focused on cricket bowling, the framework developed here has the potential for broader application. Future research could explore extending this approach to other sports, such as football, basketball, or tennis, where predicting deceptive movements plays a crucial role. Additionally, integrating real-time analysis capabilities could enhance the practical usability of virtual coaching systems, enabling immediate feedback during live training or matches. Further investigations should also consider a wider range of athlete metrics, such as energy expenditure, fatigue levels, and mental resilience. These factors, combined with biomechanical insights, would provide a comprehensive understanding of an athlete's condition, supporting personalized training strategies. Collaborations between sports scientists, psychologists, and AI researchers could unlock new dimensions of athlete performance and injury prevention. By addressing these areas, future studies can build upon the foundation laid by this research, advancing the application of AI in sports science and solidifying its role in shaping the future of athletic training.

The study highlights the potential of AI-driven virtual coaches to provide precise feedback on postural changes, indicating significant improvements in understanding and training athletes. Moreover, future research should aim to expand this framework to include assessments of energy, fatigue, and mental exhaustion, offering a holistic view of an athlete's condition. Integrating diverse evaluation techniques will further enhance these virtual tools, enabling coaches and athletes to refine training strategies more effectively.This study confirms that AI and advanced analytics are not merely tools for analysis but are instrumental in revolutionizing training methodologies. By opening new frontiers in sports science, these technologies elevate athletic performance to unprecedented heights. Despite the challenges posed by the complexity of cricket bowling techniques, the advancements made in this study pave the way for further innovations in the field, demonstrating the critical role of AI in the future of sports training and athlete development.

CRediT authorship contribution statement

Mutawa A. M.: Writing – review & editing, Writing – original draft, Supervision, Project administration, Conceptualization. **Rajesh Kumar Korupalli V:** Validation, Software, Methodology. **K Hemachandran:** Visualization, Validation, Software, Methodology. **Murugappan M.:** Writing – review & editing, Writing – original draft, Visualization, Data curation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data supporting this study's findings are openly available on the IPL's Official Website, www.iplt20.com.

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Glossary of Key Technical Words

Pose Estimation: Detecting body postures from images or videos.
OpenPose: A tool to track human body movements in real-time.
CNN (Convolutional Neural Network): A model for analyzing visual data.
Random Forest (RF): A machine learning method using multiple decision trees.
K-Nearest Neighbor (KNN): A method to classify data based on nearest neighbors.