Received: 8 March 2022 | Revised: 23 September 2022 | Accepted: 3 November 2022

DOI: 10.1002/widm.1496

ADVANCED REVIEW

WIREs DATA MINING AND KNOWLEDGE DISCOVERY

WILEY

Sports analytics review: Artificial intelligence applications, emerging technologies, and algorithmic perspective

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Funding information

National Science Foundation, Grant/Award Numbers: Career Grant # 1750936, REUGrant#2050999; U.S. Army, Grant/Award Number: Grant # W911NF2120076

Edited by: Mehmed Kantardzic, Associate Editor and Witold Pedrycz, Editor-in-Chief

Abstract

The rapid and impromptu interest in the coupling of machine learning (ML) algorithms with wearable and contactless sensors aimed at tackling real-world problems warrants a pedagogical study to understand all the aspects of this research direction. Considering this aspect, this survey aims to review the state-of-the-art literature on ML algorithms, methodologies, and hypotheses adopted to solve the research problems and challenges in the domain of sports. First, we categorize this study into three main research fields: *sensors*, *computer vision*, and *wireless and mobile-based applications*. Then, for each of these fields, we thoroughly analyze the systems that are deployable for real-time sports analytics. Next, we meticulously discuss the learning algorithms (e.g., statistical learning, deep learning, reinforcement learning) that power those deployable systems while also comparing and contrasting the benefits of those learning methodologies. Finally, we highlight the possible future open-research opportunities and emerging technologies that could contribute to the domain of sports analytics.

This article is categorized under:

Technologies > Machine Learning

Technologies > Artificial Intelligence

Technologies > Internet of Things

KEYWORDS

augmented and virtual reality, data mining, machine learning, meta learning, reinforcement learning, sports analytics, survey, zero-shot learning

1 | INTRODUCTION

The sports analytics domain is evolving, and researchers are exploring novel applications and research problems. Recently, a study[1] shows that the global sports analytics market size was valued at USD 885 million in 2020 and also shows that it will increase at 22.3% of the compound annual growth rate between 2021 and 2028 years. The article discusses that the management of the teams and players realized the significance of on-/off-field data streaming related to players' performance, game plan, injuries, training sessions, and so on, which became a necessary part of the players' betterment and team management. *Sports analytics* is the training, collecting and investigation of analytical data, and employing state-of-the-art data mining techniques to predict and determine the players' performance to determine their weaknesses and strengths in their game. Sports analytics has opened a vast spectrum of research problems and challenges, mainly covering real-time players'/team performance assessment (I. Ghosh et al., 2022), 3D pose estimation (Cai et al., 2019), game dynamics (A. Ghosh et al., 2018), tactics, behavioral and psychological study of the players in the competitive environments (Sheehan et al., 2023), and so on. Gerrard and Alamar (2014) introduce and present an overall sports analytics framework which is comprised of four main components: analytic models, data management, information systems, and the decision maker. Data management includes procedures associated with verifying, acquiring, and storing data. Analytic models include applying statistical and data mining techniques to acquired data. Information systems' aim is to extract and present the data and model inference results effectively, and decision-makers' aim is to extract relevant and insightful information from the data and present it to the coaches, players, and so on.

Sports can be defined as a collection of activities performed by an individual or a team that involves physical exertion and skills to compete against opponents. In a broad spectrum, sports can be classified into two categories: *indoor recreational sports* (badminton, snooker, chess, table tennis) and *outdoor recreational sports* (cricket, soccer, surfing). Many sports are similar in body pose, objective (to outplay their opponents), and style of play, such as tennis, badminton, and so on. For instance, a badminton game requires more players' forearm strength, whereas a tennis game requires more arm strength. Furthermore, every sport has its unique game speed, requirements, dynamics, outcome, players' power exertion, and so on. The uniqueness of each sport makes it difficult for researchers to capture and analyze those actions to develop generalized and robust data and knowledge-driven applications in the sports domain. Shih (2017) comprehensively discusses and highlights studies related to content-aware video analysis, which covers topics related to objects, context-oriented groups, actions, and events in sports. The authors provide a deeper interpretation of content-aware sports video and focus on video content analysis techniques applied in sportscasts from the perspectives of fundamentals. In contrast, we provide a holistic review of the sports analytics domain in this study. We provide application-specific fields along with applied ML techniques. We also discuss the recent trends, challenges, and future directions in the sports analytics domain. Furthermore, Claudino et al. (2019) provide and enumerate a review of applied ML techniques in sports analytics. The motivation of the study is to provide a holistic review of the current state of the application-specific of applied artificial intelligence (AI)/ML techniques in assessing the injury risk and predicting performance in team sports athletes. In another study, Sheehan et al. (2023) discuss and enumerate a holistic analysis on quantifying technical, tactical, and physical characteristics by employing structural equation modeling. The study conducted a longitudinal case study design where teams' cooperative passing network, skill counts, spatiotemporal behaviors, and physical loads are considered during Australian Football League seasons from 2016 to 2019.

Hypothetical development in AI/ML fields has contributed to information reasoning and knowledge-driven dependent algorithms to build scalable and robust decision-making systems. Integrating wearable and computer vision-driven applications with data mining techniques contribute enormously to studying the players' performance, behavioral insights, posture, dynamics of the game, and so on. Various state-of-the-art ML techniques have been applied to sensory and computer vision-based datasets to solve real-time sports analytics inference. Deep learning, reinforcement learning approaches, and so on have proven to be more effective than the classical statistical learning (SL) techniques in extracting knowledge and discovering, learning, and inferring data activities enumerated by Chakma et al. (2020) and I. Ghosh, Ramamurthy, and Roy (2020). The activities/shots can be defined as the players' micro-complex and non-periodicity limb movements, which eventually increases the complexity for real-time tracking models. *Sports analytics* covers a vast spectrum of diversified topics such as tracking and analyzing physical actions, performance, gameplay, physics dynamic-motions theories (initial/final momentum, circular motions, velocity), and so on.

The motivation of this study is to meticulously explore the recent trends in AI-related applications for the sports analytics domain. We incorporated recent research advancements in sports analytics and covered about 10+ years of related works and progress in this field. The major contribution of this study is to enumerate and provide a holistic review of applied ML techniques along and recent trends along with the challenges in the sports analytics domain. Our study is one of the few studies covering three different application-specific disciplines and applied ML techniques and summarizes challenges and future directions across the sports analytics domain. Figure 1 provides a comprehensive pictorial view of the scope of taxonomies of this study. In addition, we enumerate recent research in application-specific disciplines such as sensor-based, computer-vision-based, and wireless and mobile-based applications. Furthermore, we highlight recent research problems and challenges faced during the development of the applications. Furthermore, we explore various methodologies and ML algorithms adopted by researchers to tackle real-time challenges, followed by a comparative analysis of each discipline in the Sports analytics domain. Finally, we highlight potential challenges and research problems followed by prospective future directions in sports for AI researchers with a few novel and open-research directions. We are confident that this study includes all recent papers

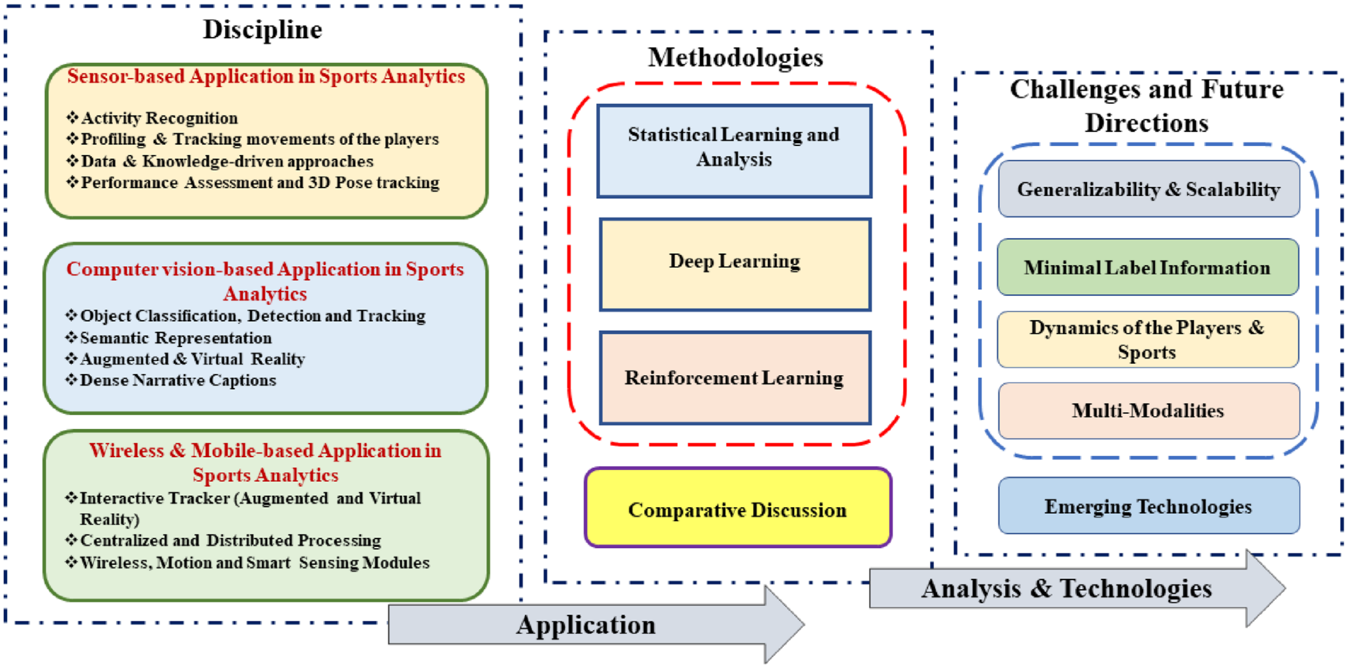

FIGURE 1 Scope and taxonomies of the study.

featured in leading journals, conferences, and workshops related to the Sports analytics domain and research groups and researchers investigating sports analytics applications.

This paper provides a comprehensive review of recent state-of-the-art techniques and challenges. It investigates the gaps between state-of-the-art methodologies to guide and motivate novel research directions. Moreover, this survey paper covers a wide range of topics and research problems and discusses AI-driven applications in sports analytics. The paper is organized as follows: in Section 2, we discuss and highlight state-of-the-art works related to various sports. Then, to elaborate in-depth, we ramified the related works in Sections 2.1–2.3, where we discussed sensor-based, computer vision and wireless and mobile-based applications, respectively. Section 3 highlights the applied ML algorithms and data-mining techniques in solving the research problems, and Section 4 examines and contrasts the above applied ML algorithms followed by future research directions and emerging technologies, and Sections 5 and 6 show conclusions of this study.

2 | DISCIPLINES IN SPORTS ANALYTICS

We categorize into three different application-specific disciplines: *sensor*, *computer*, and *wireless and mobile-based* applications across the sports analytics domain. We thoroughly discuss and summarize recent studies and research problems aligning with data mining techniques and the sports analytics field. It covers a vast spectrum of applications and problems ranging from activity recognition, profiling and tracking of players, semantics representation, object detection, centralized and distributed processing, augmented/virtual reality, and so on. We enumerate the above-listed research problems and applications in-detail in the following paragraphs. Moreover, we discuss and exhibit state-of-the-art algorithms, open-source datasets, and industrial-based wireless and mobile-based applications in Tables 1–3, respectively, and evaluation metrics are shown in Table 4 by utilizing various state-of-the-art techniques.

2.1 | Sensor-based applications in sports analytics

Recently, researchers have successfully infused real-time inference with Internet-of-Things (IoT) wearable sensors. However, human activity is unique, as the information inferred from raw sensor data has been important for functional and behavioral health monitoring sports and fitness tracking systems. However, each individual has a unique way of

TABLE 1 Academic literature on sports analytics (SA).

Literature	Descriptions	Disciplines
Li and Fei-Fei (2007)	Object recognition: eight different sports images—rowing, badminton, polo, bocce, snowboarding, croquet, sailing, and rock climbing	Computer vision based
Waltner et al. (2014)	Indoor sports activity detection video benchmark dataset for volleyball games with seven classes: service, reception, setting, attack, block, stand, defense/move	Computer vision based
Connaghan et al. (2011)	Tennis stroke recognition: strokes which were considered for the study are backhand, forehand or serve shots collected from eight players in total and further categorized into advanced, intermediate and novice players	Sensor based
Steels et al. (2020)	Total of nine activities in which seven badminton strokes and movements (clear, dab, drive, short serve, lob, net drop, smash) and two activities (running and standstill) and employed three different sensor locations: the bottom of the racket's grip, the wrist and upper arm, collected from two right-hand players: a male and a female player	Sensor based
Anik et al. (2016)	Collected and classified only three badminton strokes: smash, serve, and backhand	Sensor based
Benages Pardo et al. (2019)	Collected four tennis strokes: forehand, backhand, volley and lob strokes, and daily activities such as walking, running, jumping, bending down, standing, being seated and sitting, and collected from four males and four female participants	Sensor based
Kiang et al. (2009)	Implemented acoustic and accelerometer sensors to analyze the smash shot and determine the speed and competitiveness of the player	Sensor based
Rahmad et al. (2019)	Two badminton shots (classes) considered: hit and nonhit shots	Computer vision based
Ó Conaire et al. (2010)	Developed a framework for combining inertial and visual dataset for tennis sport and used to detect three strokes: serve, forehand, and backhand	Computer vision based
Zhou et al. (2016)	Smart soccer shoe: formulated a fabric pressure (sensor-based soccer shoe) to analyze and detect the action between the foot and ball and to soccer kick/pass expertise of the player	Sensor based
Cai et al. (2019)	Proposed HARPET (Hockey Action Recognition Pose Estimation, Temporal) and studied four types of actions in hockey games: skating forward, skating backwards, passing, and shooting	Computer vision based
Ballan et al. (2009)	MICC-soccer-actions-4: video clips with performing four frequent actions: shot-on-goal, placed-kick, throw-in, and goal-kick	Computer vision based
McNally et al. (2019)	GolfDB: video clips of golf swings from PGA, LPGA, and Champions Tours, totaling 248 individuals which eight actions: Address (A), Toe-up (TU), Mid-backswing (MB), Top (T), Mid-downswing (MD), Impact (I), Mid-follow-through (MFT) and Finish (F)	Computer vision based
Piergiovanni and Ryoo (2018)	MLB baseball dataset: consists of nine classes: ball, strike, swing, hit, foul, in play, bunt, hit by pitch and no activities	Computer vision based
H. Zhao, Wang, et al. (2019)	Tennis sports: consists of three classes: serve, ground-stroke, and volley from seven participants categorized into: coach, regular player, and casual player	Sensor based
Malawski and Kwolek (2016)	Fencing sports: collected six footwork actions (step forward, step backwards and four types of lunges: rapid, with increasing speed, with waiting, jumping-sliding) from 10 participants	Sensor based
Mlakar and Luštrek (2017)	Tennis sports: collected three different strokes (serve, forehand or backhand) from five different professional tennis players	Sensor based

performing the activities. Such a phenomenon leads to more complex problems. In that way, developing algorithms for a specific scenario is simple, but scaling the algorithm becomes a challenging problem. Another challenge is *multi-modalities problems* (multiusers, multitypes of sensing devices variability, multimodes, such as text, images, inertial measurement units [IMU], audio, or multibody positions variability). Contrastingly, very few pieces of literature solely discuss and tackle the multimodalities problem and challenges, particularly in the sports analytics domain. Furthermore, data veracity is another challenge in building data-driven applications in the sports analytics domain. Data truthfulness is one of the major components of information/intelligent systems. Cooper et al. (2007) presented a statistical procedure to determine the reliability of data in performance-based sports systems. The statistical procedure measures the absolute agreement to distinguish between the successes and errors made by the expert and is applied effectively to individual performance indicators to build sports performance systems.

TABLE 2 Open-source datasets on sports analytics (SA).

Datasets	Activities	Disciplines
I. Ghosh, Ramamurthy, Chakma, et al. (2020)	BAR dataset: collected 12 different badminton shots involving subtle movements of limbs (hand, palm, left leg, and right leg) and collected from 11 participants	Sensor based
Barshan and Yüksek (2014)	DSADS dataset: collected 19 different sports, activities of daily living (ADL)	Sensor based
Kadu and Kuo (2014)	Mocap: Motion-captured for 113 subjects performing 1095 unique activities in the following categories: human interaction, interaction with environment, locomotion, physical activities and sports, situations and scenarios	Computer vision based
Giancola et al. (2018)	SoccerNet: comprised of 500 complete soccer games and covering three seasons from 2014 to 2017 with 6637 temporal annotations are automatically parsed for three main classes of events (goal, yellow/red card, and sub-situation)	Computer vision based
Heilbron et al. (2015)	AcitivityNet: a large-scale video benchmark dataset for human activity with 203 activity classes and 849 total video hours	Computer vision based
De Campos et al. (2011)	Adaptive cognition for automated sports video annotation: smart finger and hand gesture tracking system to track the complex movement of the limbs	Sensor based
Soomro et al. (2012)	Sports action dataset: diving, golf swing, kicking, lifting, riding horse, running, skate boarding, swing-bench, swing-side and walking	Computer vision based
Andriluka et al. (2014)	MPII Pose: There are 823 different types of activities from 21 different categories, which includes bicycling, sports, dancing, running, lawn, garden, religious activities, and so on	Computer vision based
Gourgari et al. (2013)	THETIS dataset: collected 12 different tennis strokes (backhand [with two hands], backhand, backhand [slice], backhand [volley], forehand [flat], forehand [open stance], forehand [slice], forehand [volley], service [flat], service [kick], service [slice], smash) from 55 (31 amateurs and 24 experienced) participants	Computer vision based
Bloom et al. (2012)	G3D dataset: performed 20 gaming actions (golf swing, punch left, punch right, kick right, kick left, defend, tennis swing backhand, tennis serve, throw a bowling ball, tennis swing forehand, walk, run, jump, climb, crouch, steer a car, wave, aim and fire gun, flap and clap) from 10 participants	Computer vision based
Zalluhoglu and Ikizler-Cinbis (2020)	C-Sports dataset: eleven categories of sports (basketball, American football, football, handball, rugby, hurling, dodgeball, water polo, ice hockey, lacrosse, and volleyball with five different activities [passing, attack, gathering, dismissal, and wandering] for each sport)	Sensor based

Moreover, researchers tried to formulate a way to tackle challenges such as individual profiling, individual variations, and so on, where the individual variations include physical fitness, stamina, speed, movement agility, and so on. Hossain et al. (2017) proposed a SoccerMate framework for profiling the players' performance in the soccer game. They proposed a data-driven deep learning algorithm, restricted Boltzmann machine (RBM), to classify low-level soccer metrics and change point detection module to compute statistical features that will score a soccer player. I. Ghosh, Ramamurthy, and Roy (2020) proposed a K-nearest neighbors algorithm based distance error estimation approach that enables to determine if the error between the professional player and intermediate and novice player stances while playing a badminton game. They studied 12 different types of badminton strokes and stances. There are studies and state-of-the-art frameworks that investigate various racquet sports like: *badminton* (Kiang et al., 2009), *tennis* (Pei et al., 2017; Whiteside et al., 2017), *golf* (Ghasemzadeh et al., 2009), and so on where the researchers were tracking and studying the swing of the racquet using IMU sensors. However, the individual variations and external factors, such as motion and device artifacts, experiment settings, individual gameplan, tactics, and so on, can also lead to poor performance, generalizability, and scalability of the overall framework.

Finally, we highlight novel state-of-the-art algorithms, data collection configuration, and ML techniques for smart wearables and sensors in sports analytics. Bin Abdullah et al. (2012), Ermes et al. (2008), Ghazali et al. (2018), and Zhuang and Xue (2019) employed IMU-based wearable devices and designed data-driven approaches for recognition and detection frameworks instrtumental for activities of daily livings (ADLs), ADLs, and sports activities. Blank et al. (2016) proposed a system for real-time IMU signal processing and classification of shots/actions and pattern recognition problems in the sports domain. Anand et al. (2017) proposed and compared two novel approaches for the swing

TABLE 3 Smart industrial wireless and mobile applications for sports analytics (SA).

Systems	Features	Sports
Power sticker for Cricket Bat (2021)	Measures power (combined the speed, quality and twist), impact locations, bat speed (velocity) and bat twist	Wireless and cricket
MiCoach Smart ball: smart football (2021)	Improve the performance of the striking skills using ball strike, flight path, speed, and spin of the ball	Wireless and Soccer
Suunto (2021)	Outdoor features includes: GPS, weather, altimeter and sports tracking features includes: heart-rate, speed/distance, swimming, running, cycling and activity tracking (calorie burn, step counts, etc.)	Multisports
Gear Sport SM-R600 SMR600 (2021)	Tracks pedometer, exercise tracker, heart-rate tracker, water tracker	Multiactivities and sports
Vibration (2021)	Studies the angles and trajectories of those makes and misses by the players and improves the performance of the players	Wireless and Basketball
Polar M460 (2021)	Brings improvement heart-rate and smart coaching, GPS, barometer, real-time strava segments and real-time score training stress score	Wireless and cycling
Smart Band 5 MI (2021)	Tracks 11 sports mode as well as physical exercises, stress monitoring, breathing exercises and sleep monitoring	Multisports
PRAC Sporttechie (2021)	Mouthguard tracks the lactate level and improves the performance of the players during the training session	Biomedical and sports
Xiaoyu 2.0 Collang (2021)	Tracks the hand movements of the players during the training sessions and considers six different strokes- clear, slice, block, drive, smash and lift. It provides 3D player tracking and action replay characteristics	Wireless and badminton
Zepp Soccer (2021)	Measure and estimate the performance of the baseball players based on the following parameters- the bad speed at impact, hand speed max, attack angle, and the vertical angle at impact. It provides 3D player tracking and video session analysis	Wireless and baseball

detection module (a) using correlation-based feature selection using minimum redundancy maximum relevance, (b) employing novel deep learning-based algorithms (convolutional neural networks [CNNs]) and bidirectional (long short-term memory [LSTM]) architectures. They have classified the hand motions into four categories: back-swing/preparation, forward swing, follow-through, and retraction. Moreover, Sharma et al. (2017) proposed a serve analytics engine (IMU sensors) that provides feedback to players via subjectively or scoring the players. The serve engine divides the IMU signal into five serve shots action key points, that is, start, trophy pose, cocking position, impact, and finish. They also discuss in detail biomechanical aspects of serve stroke that could help the players to recognize relevant factors of improvement, or identify potential causes of injury, thus improving the performance.

2.2 | Computer vision-based applications in sports analytics

Computer vision-based applications are another booming research field where researchers build more sophisticated approaches and applications related to Sports analytics. It brings new directions in research to study the players' performance, semantics representation, and learning and recognize different game dynamics. One of the new research directions is thermal imaging to analyze the players' game and be deployed in real-time. An article[2] illustrates that thermal imaging can be used to track the movement of the limbs of the player and mark the most stressed (heat map) position of the limbs while playing the game. Thus, bringing thermal camera imaging in sports analytics helps capture the movements of the players' limbs and assessing the players' movements during the game can help them improve their game. Thermal imaging is widely used in medical-driven research in sports (Costello et al., 2013) and in biomedicine (Kirimtat et al., 2020). Kirimtat et al. (2020) conduct a comparative analysis to determine the quality of thermograms between forward looking infrared (FLIR) and Seek thermal camera to detect injured toes of the human subjects. Finally, an infrared camera can be preferred for noticeable biomedical applications. Furthermore, the novel approaches for determining and capturing vital insights such as limbs' movements, gameplay tactics and style and features of the players gave the researchers a cutting-edge approach toward studying semantic knowledge, reducing injuries, and

TABLE 4 Evaluation metrics.

Literature	Definition	Task
Steels et al. (2020), Benages Pardo et al. (2019)	Represent the tradeoff between precision and recall scores. The high area under the *Precision-Recall Curve* represents both high recall and high precision. High precision correlates to a low false-positive (FP) rate, and high recall correlates to a low false-negative (FN) rate	Classification
I. Ghosh et al. (2022); Chakma et al. (2020)	*F1 Score* is compute by combining the precision and recall scores by computing the harmonic mean between the scores	Classification
Cai et al. (2019)	*Percentage of Correct Keypoints Pose Estimation* measures the predicted keypoints, and the true joint is within a certain distance threshold. It is usually set w.r.t. the scale of the subject, which is enclosed within the bounding box	Human-pose estimation metric
Yu et al. (2018)	*Fine-grained Captioning Evaluation* metric considers not only the linguistic scores of the sentence (coarse-grained video caption tasks) but also whether the key motion and the order of the movement are correctly judged	Fine-grained video captioning
Wu et al. (2020)	*Err* metric used to determine the ankle rotation and lateral movement. It provides error values for the ankle rotation and represents the offset between the target value in degree and for the lateral movements in meters	Virtual reality
Fu and Liu (2013)	*Collision* occurs when more than one device tries to send a packet on the network at the same time. *Packet loss* means the loss of data packets that do not reach the receiver after being transmitted across a network	Wireless networking
Liu and Schulte (2018)	*Game Impact Metric* (GIM) scores evaluate the players' performance and measure both players offensive and defensive contribution to goal scoring	RL-based players' evaluation and ranking
A. Ghosh et al. (2018)	*Segmental Edit Distance Score* metric measures the correctness of the predicted temporal ordering of actions and also is computed by applying the Levenstein distance to the segmented predictions	Action segmentation
Vats et al. (2020)	*Mean average precision* (mAP) employ to compare the ground truth bounding box to the detected box and returns a score. The higher this score, the more accurate and closer the candidate to a target, and the better the spotting performance	Action spotting
Voeikov et al. (2020)	*Euclidean distance* (RMSE) is employed to estimate to the difference between the predicted and labeled ball position computed over true-positive (TP) ball detections	Object (Ball) position detections
Luo et al. (2020)	*Action Impact Scores* are adopted as a function of the game context (Markov state) and measure how much an action improves over the average action	RL-based players' evaluation and ranking

analyzing the players' performance in the game (Thomas et al., 2017). Another new research direction is developing augmented reality and virtual reality (AR/VR) game consoles in computer vision-based applications. Bideau et al. (2010) and Wu et al. (2020) developed a virtual reality game console to educate and improve the players' performance by familiarizing them with real-time environments and also providing a better understanding of the game which eventually improved the players' gameplay tactics and actions.

Due to enormous public datasets, deep learning algorithms prove a better alternative to traditional computer-vision algorithms to solve various research problems and challenges. A few of such research problems are *object classification* (Chu & Situmeang, 2017), *object tracking* (Moon et al., 2017), *object segmentation* (Bin Abdullah et al., 2012), *object detection* (Reno et al., 2018), and so on. Furthermore, interestingly, FarajiDavar et al. (2011) introduced an action recognition classifier using transductive transfer learning. They have employed HOG3D features to define the actions and a feature reweighting technique on the source domain features based on the joint expectation of features and class labels in the source and target domains. They introduced complex feature transformation techniques, that is translation and scaling, to improve the accuracy and transferability of knowledge from source to the target domain. Moreover, Holbrook et al. (2019) developed a model Ruby-Bot by employing multitask learning, and the architecture of the proposed model is a mixture density network. The end goal of their study is to capture and fuse the spatial and contextual information to make predictions about the outcome of the game. Nistala and Guttag (2019) designed an unsupervised deep learning pipeline that helps to study the pattern of the players on the offensive using six camera tracking systems to track the real-time positions of the players. They designed a CNN-based autoencoder that can generate the trajectory embedding to understand how players move on attack or offense during the game. One of the most exciting and challenging problems in computer vision is real-time inference for movement tracking and pose estimation in the sports analytics domain. Einfalt and Lienhart (2020) and Vats et al. (2020) developed a system to track the movements of the players.

In the following review papers, D'Orazio and Leo (2010) and Manafifard et al. (2017) discussed tracking the players, which included different tracking frameworks and preprocessing—high- and low-level features analysis. They broadly discussed and studied the state-of-the-art techniques and articulated the weaknesses and strengths of various existing frameworks in the sports domain. Furthermore, Ó Conaire et al. (2010) combine the inertial and visual data to extract both the temporal location of tennis strokes and subsequently classified the tennis strokes as being either a serve, forehand, or backhand. Similarly, Vanderplaetse and Dupont (2020) developed a multimodal system in which they combined audio and video data for soccer games, which eventually improved the performance of the system for detecting soccer actions spotting and tasks. They employed ResNet and VGG to capture the feature representations from video and audio data. Finally, Tsunoda et al. (2017) discussed a hierarchical LSTM which can be employed for action recognition (pass, dribble, shoot, clearance, loose ball) in the game of football. Furthermore, computer-vision (CV)-based techniques and applications in the Sports analytics domain are still emerging day-to-day, along with new challenges.

2.3 | Wireless and mobile-based applications in sports analytics

We focus on the wireless and mobile-based applications solely developed for sports analytics and briefly explain various concepts and novelties in this domain. Wireless and mobile-based applications are an emerging research area that has attracted researchers related to different domains. Majorly, the wireless and mobile-based systems are comprised of four components: user interface, computational component and connectivity, physical processes/sensors, which include wireless sensing, embedded sensors, and tracking and analysis of the physical motion in real time as shown in Figure 2. There is much ongoing research for embedded systems in sports, smart cities, industrial internet, and so on. Furthermore, it gave the researchers a cutting-edge in motion tracking, sensing, and assessment. Therefore, the researchers can develop a generalized system used in the different domains.

Furthermore, we articulate and discuss recent development and proposed studies for mobile and wireless applications in the sports domain. Hsu et al. (2018) developed a sensor-based network embedded system module in which they can capture the movements of the limbs to recognize those movements. The wearable sensor network architecture consists of three operation modules: sensing system, micro-controller, and wireless (radio frequency) transmission. Moreover, Valade et al. (2016) developed two generalized embedded systems: centralized and distributed processing which can be used in various sports. The proposed system focuses on multisports capabilities, beginning with tri-athlete

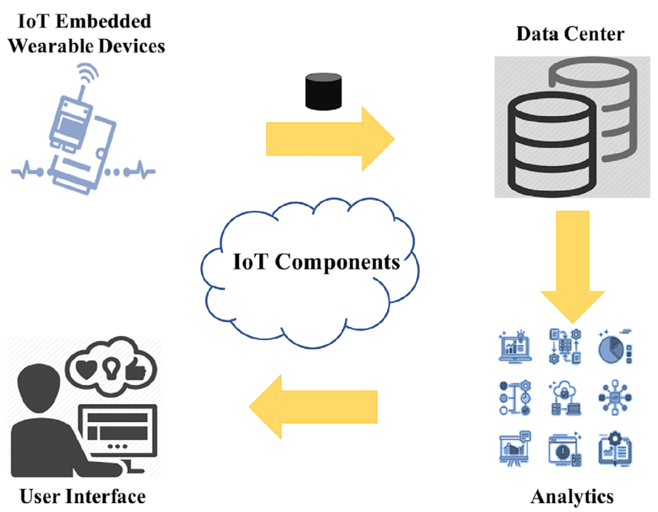

FIGURE 2 Figure gives a pictorial overview of the pipeline for each component of the wireless and mobile-based applications. Four major components are sensing module (IoT wireless and sensing devices), data center and processing, machine learning (ML) algorithms and user interface (Hsu et al., 2018; Ikram et al., 2015).

equipment. Several pieces of research have been developed along with the domain of the sport as proposed by Gowda et al. (2017, 2018). The authors proposed a system iBall with wireless, motion, and sensing modules for the game cricket that track the rotation/spin of the ball and track the players in the field. Burke (2019) introduced a DeepQB system which used to track the player and also quantify quarterback decision-making which stimulates to improve the performance of the player in the football game. In this approach, the system showed a new path for the players, team, and so on to understand the quarterback decision-making, which was previously unavailable in the sport.

Similarly, Ikram et al. (2015) proposed an IoT-based system for soccer, which successfully monitors the players' game so that during the game plan, injuries, and so on, these aspects can be analyzed and provide insights into the game. The pipeline of the proposed framework consists of a sensing module (Radio Frequency Identification [RFIDs] and physiological sensors), telecommunication technology (ZigBee), and cloud computing and a user interface for monitoring the game. Similarly, Fu and Liu (2013) proposed a monitoring system for various sports activities. To build the monitoring system, they employed photoplethysmography-signal body sensor networks—bodynets, wireless sensing RFIDs, routers and mesh nodes, servers, and processors. Finally, there are emerging technologies and open-research problems, and still, the embedded systems field is challenging, particularly for the sports analytics domain. In contrast, significant advancements paved the industrial-based embedded systems available across the market.

In comparison, industrial wireless and mobile applications state-of-the-art devices are gaining immense popularity among the coaches and players. One of the such study is Spektacom (2021), who introduced a smart sticker for cricket bats that improves the performance of the players, and the advantage of this novel smart sticker is that the coaches and players get real-time insights by introducing profiling and capturing the practice sessions of the players. Likewise, Fastpong (2021) introduced an interactive table tennis tracker device that tracks and improves the performance of the player. Furthermore, they also have user interface software to determine session scores, weaknesses and strengths. Furthermore, sports giant companies like Nike (2021) introduced a large number of wearable sensors for multisports and to track physiological sensing like heart rate, stress-sensing, and so on. Nowadays, the availability and affordability of sports tracking systems are becoming popular among players and coaches. Similarly, in the study of Simi (2021), a high-end image-based motion capture and analysis system provides essential properties like sports biomechanics, athlete screening, match and tactical analysis, and so on. The following section discusses and articulates state-of-the-art algorithms and methodologies adopted in the sports analytics domain.

3 | METHODOLOGIES IN SPORTS ANALYTICS

This section enumerates and discusses various applied ML techniques across *Sports Analytics* domain. We discuss in-depth encircling *SL*, *deep learning* and *reinforcement learning* techniques. We noticed that majorly the researchers adopted the following algorithms for various sports analytics applications. Interestingly, we discovered that irrespective of advancements in deep learning and reinforcement learning algorithms, still we found that SL is famous among the coaches for its simple and easy interpretable characteristics.

3.1 | Statistical learning

SL has unfolded new research directions in the sports analytics domain and other various big data sports field (L. Pan, 2019). For instance, Xia et al. (2017) discuss how statistical techniques such as variance, entropy, and min/max values can be utilized for analyzing the players' movements and their performance. Statistical techniques such as variance, min–max values, standard deviation, and so on highlight important attributes which are helpful and important for the individuals and team management to determine the players' performance. For instance, variance and standard deviation provide interesting insights which measure and estimate the attributes (body posture, style, speed) and determine the most error-prone features of the individuals' during the training sessions. SL bridges the gap between the players' performance and analytical tools. The few most practiced statistical analysis methods are mean, median, mode, sample size determination, hypothesis testing, and so on. Moreover, there are publicly available books,[3,4] which are solely based on statistical methods in sports. Recently, coaches and sports data analysts have been inclined toward using traditional statistical techniques to determine or analyze the players' performance.

Furthermore, numerous works have been done to profile players in various sports. For example, in an article[5], authors highlight how statistics and numbers are getting over the traditional ways of improving and analyzing the performance of the players. Recently, the researchers are focusing on bringing data-driven models and statistics to determine the players' performance insights. For example, Maszczyk et al. (2014) performed a comparative analysis for predicting javelin throwers and predicting the result of the game. The correlated matrix showed that the four independent variables (specific power of the arms and the trunk, cross step, specific power of the abdominal muscles and grip power) vary the performance of the javelin throwers. In another study, Hossain et al. (2017) developed the players' profiling system using wearable devices. They employed a deep learning algorithm, RBM, to classify low-level soccer metrics and proposed a change point detection module to compute seven different statistics attributes to score a player in a soccer game. Moreover, recently the researchers focused more on bringing ML techniques with mathematical inference to bolster the performance of the players' body orientation (Arbues-Sanguesa et al., 2020), error estimation (I. Ghosh, Ramamurthy, & Roy, 2020), and players' profiling (Hossain et al., 2017).

However, we believe that SL lacks robustness, scalability, and generalizability characteristics as it requires a large labeled dataset (Tuyls et al., 2021). Therefore, it becomes one of the significant challenges for researchers to mitigate the problem in a real-world environment. Furthermore, another challenge is domain-specific knowledge, as the researchers require domain knowledge to extract meaningful statistical attributes which can define and estimate the performance or gameplay of the players. Due to the above challenges and advancements in recent ML algorithms, researchers are inclining toward deep learning (CNN, recurrent neural network [RNN], gated recurrent unit), reinforcement learning, and so on. Moreover, researchers are developing more robust, generalized, and scalable frameworks that can easily be trainable and deployed in real-time scenarios. We will highlight recent advancements in deep learning and reinforcement learning techniques in the sports domain.

3.2 | Deep learning

Deep learning gained immense popularity due to the generalizability and scalability characteristics compared to the traditional ML and SL analysis methodologies. Researchers successfully showed that the deep learning algorithms are better compared to the traditional ML algorithms (Chakma et al., 2020; Faridee et al., 2018), particularly in the domain of complex feature representation learning (Bengio et al., 2013) and performance (I. Ghosh, Ramamurthy, & Roy, 2020). In deep learning, the raw features are learned automatically by performing some nonlinear activation functions and shift-invariant transformation functions, which helps retrieve better feature representation than the traditional learning algorithms. Moreover, the precision of the handcrafted features depends on the domain knowledge of the researchers. Therefore, the feature extraction and selection methodologies are essential in building a robust data-driven ML model, particularly for a real-world situation.

Deep learning hugely contributed to the sports analytics domain. Few popular deep learning approaches, which include convolutional neural networks (ConvNets), RNNs, LSTMs, and gated recurrent units, are mostly employed to study the spatial and temporal research problems. ConvNets are vastly used for spatial-based research problems such as images, whereas RNNs are vastly employed for temporal-based research problems. Moreover, ConvNets are feed-forward-based neural networks that utilize pooling layers and filters to extract meaningful features. Furthermore, Equation (1) represents the steps of the convolution layers operation, where X represent the input matrix of input data and k represents the kernel size of the layer. A convolution layer is a product of one matrix of learnable parameters and another matrix called kernel producing an activation map, as shown in Equation (1). Similarly, RNNs perform the operations based on the information from prior inputs to influence the current input and output by using internal memory. Moreover, in Equation (2) where X_t is the input at time step t (t_{th} is the element of the input sequence), h_t is the hidden state at time step t, and y_t is the output at time step t, a_s and a_o are activation functions at the respective layers. Equation (2) shows that the state of the recurrent neural network is an output of the hidden layer and depends on previous inputs and hidden states.

$$f[y,n] = [X^{*}k][y,n] = \sum_i \sum_j k[i,j]X[y-i,n-j], \tag{1}$$

$$\begin{aligned} h_t^{\mathrm{in}} &= X_t W_s + h_{t-1} U + B_s, \\ h_t &= a_s\left(h_t^{\mathrm{in}}\right), \\ o_t^{\mathrm{in}} &= h_t W_o + B_o, \\ o_t &= a_o\left(o_t^{\mathrm{in}}\right). \end{aligned} \tag{2}$$

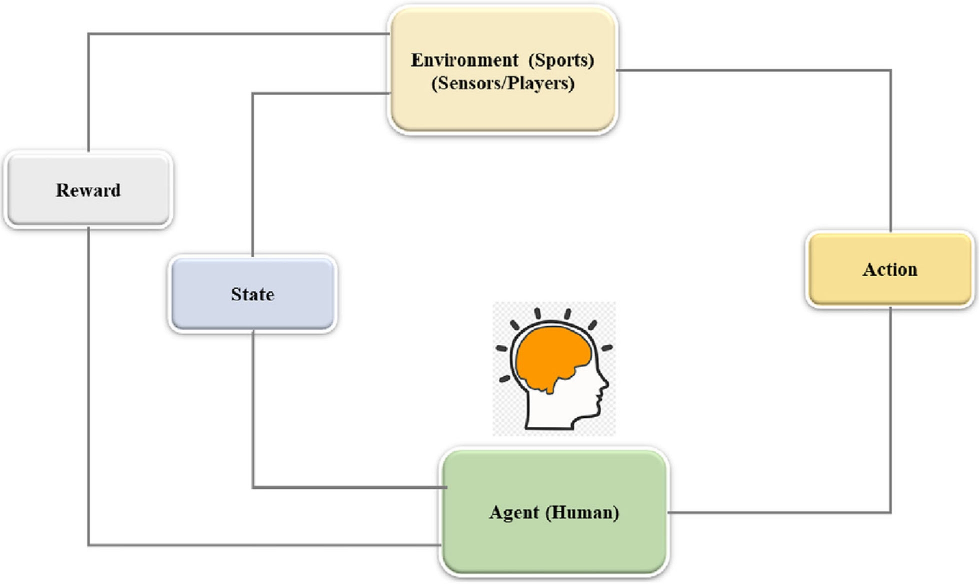

FIGURE 3 Building blocks of reinforcement learning cycle.

A. Ghosh et al.'s (2018) proposed module is based on a data-driven scoring approach, which depends on the reaction, speed, and footwork of the badminton player during the game. They proposed a hierarchical classification method in which they employ temporal CNNs to detect and track the players and classify the strokes. Studies show that the CNN algorithm performs efficiently and exceptionally for spatial and temporal research problems. Moreover Von Braun et al. (2020) employed Mask R-CNN architecture to detect waterline detection in canoe sprint games. The authors employed a pretrained Mask R-CNN architecture for canoe semantic segmentation and adopted a multistage approach to determine the waterline from the canoe segmentation. Moreover, Voeikov et al. (2020) proposed a semantic segmentation multitask neural networks architecture to process down-scaled HD table tennis sports videos with a multitask labeled dataset to analyze and detect the semantic segmentation masks, ball coordinates, ball detection, and events.

3.3 | Reinforcement learning

Reinforcement learning is one of the ML techniques that is still evolving. It is based on where the agent moves to take action associated with a state in an interactive environment to receive a reward. The motivation and goal of the agent are to maximize the reward received. Maximizing of reward can be achieved in two ways: exploration and exploitation, where exploration means exploring the sample space, is based on global search, whereas exploitation means improving or refining the achieved reward score and is based on local search. Figure 3 depicts the building blocks of the reinforcement learning algorithm. Reinforcement learning can be mathematically represented as the Markov decision process (MDP tuple $= (S, A, S_i, R, \gamma)$), where the agent executes an action (A) in an interactive environment, from the current state (S) and to the successor state S_i, R represents the reward function associated with each action, and γ is the discount factor $\in [0, 1]$.

Reinforcement learning techniques are gaining immense popularity and have unfolded a new research direction for researchers. Wang et al. (2018) developed a framework to study double teams in the National Basketball Assocation (NBA) game and coined a deep-reinforcement learning model that minimizes the score/reward achieved by the offense. Similarly, Luo et al. (2020) proposed a framework by fusing Q-function learning and inverse reinforcement learning (apprenticeship learning) to develop a novel ranking method. They also leveraged single-agent inverse reinforcement learning for multiagent ice hockey Markov game by an alternating learning framework. They also employed a transfer learning technique to transfer the knowledge between the multiple reward functions for the same task. Similarly, Liu and Schulte (2018) adopted a deep reinforcement to learn an action-value Q function learning and the learned Q-function is employed to value the players' actions under different game contexts. In order to integrate the context signals and game history, they used dynamic LSTM architecture. They devised a novel overall players' evaluation metric known as a game impact metric (GIM).

In the paper of Y. Zhao, Borovikov, et al. (2019), the authors proposed hierarchical learning with a multiagent reinforcement framework. The study aims to attain a skill level and style similar to the humans in sports games. They have categorized hierarchical learning into two subproblems: high-level and low-level problems. In low-level problems, agents need to perform similar to humans, which is achieved by imitation learning. Like the high-level problem, the agents need to follow a game plan, which is achieved by reinforcement learning. Similarly, in the paper of Jia et al. (2020), the authors proposed an integrated curricula training framework, deep multiagent reinforcement learning for a fever basketball sports environment. The study's primary goal is to solve the asynchronous real-time problems, supporting both single-agent and multiagent training.

4 | COMPARATIVE ANALYSIS OF THE APPLIED ML ALGORITHMS

This section provides a comparative study of application and algorithms-oriented challenges and problems faced in developing sports analytics applications. For example, there are a few challenges like zooming the image, blur, shadows, reflections, and so on, which are generally faced in computer vision-based applications. In contrast, challenges like the start and end time of the activity, motion, and device artifacts, and so on are a few challenges faced in sensor-based applications. Furthermore, these challenges are more application-oriented but can deter the performance of the AI/ML algorithms. Moreover, challenges such as large unlabeled datasets, high computational, memory and time complexity, fewer labeled data, sparse datasets, class imbalance, and so on are some challenges that are mostly faced during the development of methodologies and algorithms.

Deep learning gained immense popularity among the other algorithms due to extracting deep and meaningful features from the raw data. On the other hand, SL solely depends on the handcrafted features (mean, variance, median, etc.) and statistical tools to determine and learn the features from the raw data. However, deep learning architecture requires high time and memory overhead complexity, due to which we require high computational resources. Moreover, another challenge is to tune the hyper-parameters to obtain better performance and optimization of the architecture. Another challenge could be feature engineering and selection also plays a vital role in better feature space representation of the raw data. Feature engineering and selection require domain-specific knowledge and expertise to acquire a better semantics inference of the raw data. Furthermore, deep learning encounters problems such as class imbalance, data size limitation, label dataset, and so on. Moreover, these challenges are very commonly faced while developing scalable algorithms. Such challenges can be tackled by employing other methodologies such as *active learning*, *transfer learning*, *self-supervised learning*, *zero and few-shot learning*.

However, along with various challenges, Reinforcement learning helps to solve more complex problems across various applications such as video games, augmented and virtual reality (AR/VR) control sets, navigation, and so on. However, Reinforcement learning requires a large chunk of data to learn and high computational resources, which can be one of the significant challenges for real-time deployment. Another challenge is the feature space dimensionality; Reinforcement learning limits itself, which also causes a challenge in a real-world deployment. Another challenge is the reward function structure, which helps agents learn the environment. Contrastingly, Reinforcement learning leads to learning the ideal behavior of the agent within a specific environment and with maximum performance. Therefore, the Reinforcement learning approach should be appropriate when we require the agents to explore and exploit and then collect information/reward and interact within the environment. Moreover, in recent times, approaches such as *imitation/inverse reinforcement learning*, *policy optimization and gradient*, *deep Q neural network*, *distributed reinforcement learning with quantile regression*, and so on are gaining popularity to solve the few challenges discussed above. The following section highlights a few unexplored research directions in the sports analytics domain.

5 | CHALLENGES AND EMERGING TECHNOLOGIES

After extensively investigating the state-of-the-art applications developed across the *sports analytics* domain, we highlight and elaborate on various promising future research directions and challenges, which will help the readers acclimate and choose from those research problems. Figure 4 enumerates and highlights the three different application-specific disciplines along with research tasks for *sports analytics* domain. The goal is to demonstrate and enumerate various open research tasks for three different application-specific disciplines: *sensor*, *computer*, and *wireless and mobile-based* applications. We also highlight and discuss a few of the research challenges below:

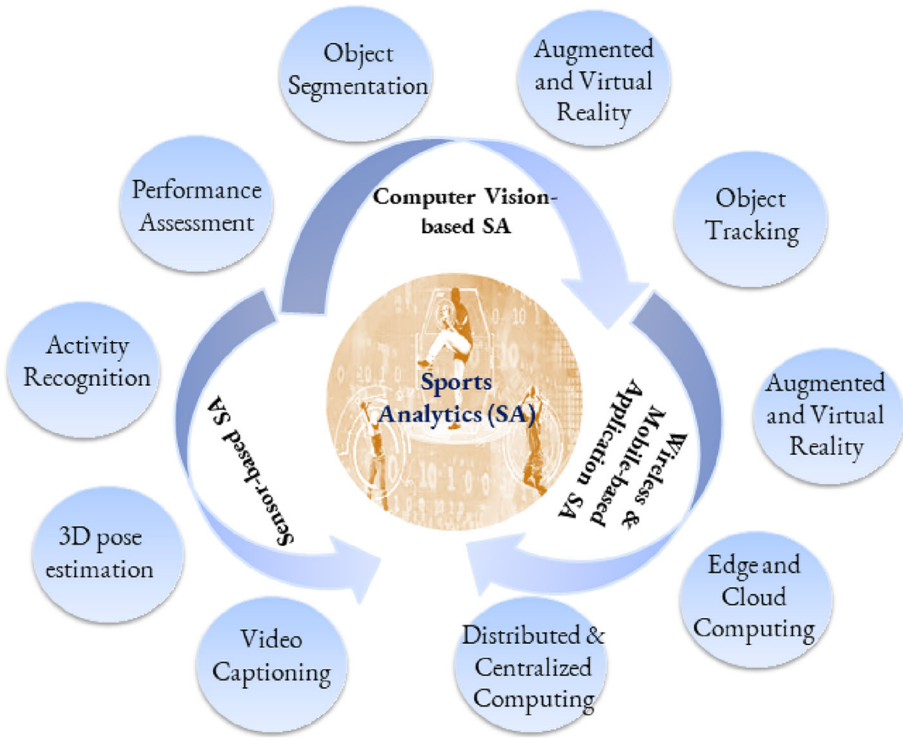

FIGURE 4 Application-specific disciplines and research tasks.

5.1 | Generalizability, transferability, and scalability characteristics

Our study has uncovered that the above characteristics are mainly lacking in the recent state-of-the-art proposed architectures. Ballan et al. (2009), Piergiovanni and Ryoo (2018), Steels et al. (2020), and H. Zhao, Wang, et al. (2019) primarily focused on badminton, tennis, soccer, and so on and proposed state-of-the-art algorithms with respect to a particular sport. As a result, the researchers lack generalizability, transferability, and scalability as they only focused on a specific sport. Recent trends show algorithms like transfer learning (S. J. Pan & Yang, 2010) and domain adaptation (Khan et al., 2018) can be useful in these scenarios. Papers show promising results in efficiently transferring knowledge of one domain to another by employing feature representation learning or probability distribution of source and target domain. Moreover, to achieve promising results, the researchers can also adopt approaches such as semantics representation and learning, scene graph relationship, and generation and context-awareness, which can also be employed to learn feature representation of the region of interest (ROI) and then try to understand and transfer that information to the target domain. Domain in our case can be players or sports which similar style and dynamics, such as racquet sports (badminton, lawn tennis, squash, etc.). Due to the lack of available related papers, it became a potential research task. Finally, it can be extended to another research problem, using minimal ground-truth or label information and building robust and generalized sports applications.

5.2 | Minimal label information

Another promising future trend could be using minimal label information and building a robust adversarial model to noisy label data. Recent trends show that various algorithms minimize the human annotation overhead cost and errors. For example, techniques such as self-taught learning (Raina et al., 2007), unsupervised learning, self-supervised learning, zero-shot (Xian et al., 2018), and few-shot/meta learning (Garcia & Bruna, 2017) are widely employed across various domains. In contrast, this particular research task is still not addressed in state-of-the-art methodologies. Nevertheless, there are associated problems such as data variability and constraints, players and sports dynamics, model selection, feature engineering, and so on. The above issues can deteriorate the proposed methodologies' performance in extracting meaningful information from source domains by employing minimal label information and transferring the knowledge to different target domains.

5.3 | Dynamics of the players and sports

As per our knowledge, fewer works investigate and discuss the dynamics of the players and sports, which covers a vast spectrum and discuss important factors such as players performance, players' teamwork, opponent analysis, individual behavior—mental and physical stress. Similarly, sports like racquetball, lawn tennis, badminton, and so on have a similar style of playing, but each sport is unique and has a different style, speed, rules, and so on. Furthermore, Burke (2019), Maszczyk et al. (2014), and Sharma et al. (2017) discussed and proposed frameworks that investigate the performance of the players irrespective of other external factors such as opponents' analysis or individual behavior (mental and physical stress). In contrast, we believe that individual behavior, psychological and physical stress, and game awareness are vital in an individual's game performance. Therefore, studying such a phenomenon can be a potential future research direction where researchers can fuse multimodalities to determine an individual's behavior.

5.4 | Fusion of multimodalities (IMU, acoustics, NLP, CV-based applications)

Another prospect for future research can be fusion multimodalities. The fusion of physiological (IMU) signals and computer-vision techniques has proven beneficial in determining an individual's emotion and facial expression in a competitive environment. Furthermore, we can extend this research approach to the sports analytics domain to determine the players' behavior (mentally and physically). In Lin et al. (2020), the authors proposed a classification framework based on the fusion of acoustic and IMU sensors. In addition, they introduced a voiceprint-based algorithm to determine the impact time of the shuttlecock hitting the racket. They employed traditional ML classifiers; naive bayes, random forest and minimal sequential optimization (SMO). The results show that the voiceprint-based approach improves stroke detection accuracy more than the commercially available devices. Moreover, multimodalities can be extended to investigate to generate dense captions or narratives for sports videos. Qi et al. (2019) and Yu et al. (2018) have generated fine-grained dense text narratives for sports videos. The authors employed attention mechanisms to generate motion modeling and group relationship/contextual information. The following frameworks capture semantic representation or ROI from the video and use attention mechanisms to focus on the ROI and generate natural language captions. We believe that the dense video descriptions can generate sports journalism, which will help the sports journalists, readers, and aspirants understand the game and eventually help a wider social impact.

5.5 | Emerging technologies

We want to highlight and scrutinize a few emerging technologies for various ML algorithms across various other domains and incorporate those algorithms into our above-discussed research problems. Recently, deep imitation learning, reinforcement learning, and so on have gained popularity among the AI/ML track researchers. Le et al. (2017) introduced a data-driven deep imitation learning approach where they developed fine-grained stimulation defensive behavior. They also demonstrated that the proposed framework could be scaled to different sports, including football and basketball. Moreover, to learn the fine-grained behavior for each timestamp, they employed LSTM, a deep learning algorithm. We believe that deep imitation learning, policy gradient, reinforcement learning, and so on can develop effective and robust feedback and recommender systems for the players. Getting assistance or feedback from a coach is very expensive during training sessions, so any feedback from a smart-assistance gadget will improve and boost the players' performance. Therefore, smart-assist gadgets with tracking and feedback features will make them affordable and bolster one's confidence to play. Moreover, one of the other recent trends is *attention mechanisms* (*self-attention*, *hard attention*, *soft attention*, *multihead attention*). Moreover, in recent related works, Qi et al. (2019) and Yu et al. (2018) discuss how attention mechanisms could be used effectively to generate dense text captions for videos. Finally, techniques such as *attention mechanisms*, *transformers*, *meta-learning*, *imitation learning*, and so on are a few of the methodologies that researchers can employ to tackle various research problems such as dynamics of the players, fusion of multimodalities, minimal label supervision, and so on.

Another research emerging technology is AR/VR in the sports analytics domain. Wu et al. (2020) proposed a VR game console to educate and improve the performance of the players. AR/VR provides a next-generation experience and familiarizes the players with the respective sports. AR/VR platform is also used as a stimulator for professional players to learn the game plan and acquaint themselves with real game scenarios. Other emerging techniques, such as semi-supervised, self-supervised learning, contrastive learning (Koshkina et al., 2021), and so on, are gaining immense popularity among researchers. In recent studies, Ludwig et al. (2021) adopted self-supervised learning to learn the feature representation from the unlabeled images and used it to estimate the 2D human pose for long and triple jump sports. They utilized two methods of self-supervised a mean teacher approach and generating pseudo labels from the unlabeled images. Similarly, Koshkina et al. (2021) introduced a novel approach to contrastive learning to learn the semantics representation from the hockey sports videos. They adopted an unsupervised contrastive learning approach to evaluate players' detection and classify teams. They also showcased team-conditioned heatmaps of players positioning during the game, which will be helpful to the coach in understanding and sketch the game plan. Finally, there are many ongoing and open-research problems and emerging technologies across the sports analytics domain.

6 | CONCLUSION

This study covers various topics related to AI in the sports analytics domain and various applications based on data mining techniques and ML algorithms. We illustrate that AI presents cutting-edge technologies to solve complex and real-time challenges in the sports analytics domain, and utilizing the technologies discussed above, the researchers successfully build robust data-driven and decision-making applications in the sports domain, as we say. This study discusses and articulates three different application-specific disciplines: *sensors*, *computer vision*, and *mobile-based applications* developed across the sports analytics domain, which is still evolving every day. First, we discuss sensor-based novel applications and articulated various approaches, followed by computer vision-based novel applications and various approaches adopted in the sports analytics domain. Finally, we enumerate and highlight a few novel wireless and mobile-based state-of-the-art systems. We also summed up a comparative discussion covering all the approaches and algorithms in sports analytics. Finally, we highlight and enumerate a few withstanding futures and promising research directions and emerging technologies that are still unexplored. We encourage researchers to employ the above-discussed methodologies and algorithms to tackle various real-world problems and challenges.

AUTHOR CONTRIBUTIONS

Indrajeet Ghosh: Conceptualization (lead); methodology (lead); resources (lead); validation (lead); visualization (lead); writing – original draft (lead); writing – review and editing (lead). **Sreenivasan Ramasamy Ramamurthy:** Methodology (supporting); resources (supporting); visualization (supporting); writing – review and editing (supporting). **Avijoy Chakma:** Methodology (supporting); resources (supporting); visualization (supporting); writing – review and editing (supporting). **Nirmalya Roy:** Formal analysis (equal); funding acquisition (lead); supervision (lead); writing – review and editing (supporting).

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest with any of the companies or products mentioned in this study.

DATA AVAILABILITY STATEMENT

We do have any data to share for this study. Thank you.

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ENDNOTES

[1] https://www.grandviewresearch.com/industry-analysis/sports-analytics-market

[2] https://www.theguardian.com/science/video/2018/feb/13/detailed-thermal-imaging-reveals-heat-map-of-a-badminton-player-video

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How to cite this article: Ghosh, I., Ramasamy Ramamurthy, S., Chakma, A., & Roy, N. (2023). Sports analytics review: Artificial intelligence applications, emerging technologies, and algorithmic perspective. *WIREs Data Mining and Knowledge Discovery*, e1496. https://doi.org/10.1002/widm.1496