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Innovating a Centuries-Old Sport: How Emerging Data Analytics Tools Are Redefining Cricket

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Column Editor's Note: *Cricket is one of the oldest organized sports in the world, but has only recently been the subject of serious data-analytics methods. Kavya Shah and Ammaar Saeed explain how data science has begun making inroads into video analysis, decision-making, and player evaluation that have the potential to enhance gameplay and provide a better experience for cricket fans worldwide.*

Keywords: cricket, highlights, sports analytics, computer vision, deep learning

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The sport of cricket originated in England in the late 16th century (Birley, 2013; Swanton, 1962). Traditionally, cricket has been played in the Test format, in which two teams of 11 players play a four-innings match that can last from 2 to 5 days (Bond, 2013). At the beginning of the 20th century, cricket established a strong foothold in the English colonies. The International Cricket Council (ICC) was formed in 1909 to regulate international cricket rules, with England, Australia, and South Africa as its founding members (ICC, 2022). A few decades later, limited-overs matches designed to be completed in one day—in contrast to the variable length of Test matches—were introduced. The first international limited-overs match was played in 1971, which led to the creation of the ICC World Cup in 1975 (Roberts, 2019).

The ICC World Cup was instrumental in spreading the global appeal of limited-overs cricket. As limited-overs cricket has become more popular, the sport is increasingly being televised to international audiences, leading many professional and amateur sports analysts to develop novel cricket data analytics methods. These tools allow cricket teams to use data to understand their strengths and weaknesses, in turn enabling them to make adjustments and enhance their gameplay in new directions. The application of data analytics to cricket has generated important contributions to video summarization, classification, prediction, and decision-making, which we review in this article.

Automatic Highlights: Applying Video Summarization to Cricket Footage

Cricket highlights are short clips that showcase the most important and interesting aspects of a match. The three cricket events usually shown in highlights are wickets, in which a batsman is dismissed; fours, in which a batsman hits a ball that bounces and then travels beyond the boundary of the field; and sixes, in which the batsman hits a ball outside the field boundary without it bouncing. Typically, creating cricket highlights is a laborious process that requires sports broadcasters and video editors to manually parse through hours of footage to identify exciting moments (Saskovec, 2022). Over the past two decades, however, researchers have built and improved upon techniques to automatically generate cricket highlights. Automated highlights generation presents a commercially useful application of computer vision and deep learning models. Video summarization is also useful for players, coaches, and organizations: film analysis of past games is an important aspect of training, and auto-generated highlights allow players to focus on only the most important segments of past matches (ScoreBreak, 2022).

Semantic Segmentation

Semantic segmentation is a computer vision task in which specific regions of an image or video are grouped into one of several categories. For the purposes of generating cricket highlights, semantic segmentation is useful for classifying frames of cricket footage and only selecting frames labeled with 'exciting' classes to be in the highlights video.

One of the first studies of semantic segmentation for cricket highlights generation involved the creation of a hidden Markov model (HMM) classifier to detect and classify exciting footage into the categories of 'ball movement,' 'fielding,' and 'wickets' (Kolekar & Sengupta, 2004). Using an HMM is advantageous compared to traditional classifiers because it utilizes previous frames, making it robust to misclassification of outlier footage. By using the estimated motion in each cricket frame as a likelihood function for the classifier, Kolekar and Sengupta achieved an 87.5% average out-of-sample classification accuracy.

In a follow-up study, (Kolekar et al., 2008) proposed a hierarchical framework to detect and classify exciting footage, which they call "events" (Kolekar et al., 2008). They created a five-level tree classifier that makes use of audio, video, and color features to label frames. By employing a hierarchical tree framework, the authors reduced the computational complexity of their classifier by only considering a small number of features, such as the density of green pixels for detecting 'field views,' at each level of the tree. This classifier achieved an 80+% out-of-sample recall (number of correctly classified events divided by the total number of events) across all five levels. While the accuracy of this classifier was lower than their previous model for certain categories, it greatly improved upon their previous work by delivering much more detailed classifications, ranging from the region of the field displayed to the type of player in frame.

While using more features can provide a higher classification accuracy for cricket footage, it can be difficult to extract many of these features with a high degree of accuracy. For example, many current highlights generation algorithms attempt to detect specific symbols or logos, which are often present on-screen for less than one second, or compute player trajectories, which can be unreliable in frames with a lot of motion. Tang et al. (2011) circumvented this issue by proposing a semantic event detection and classification method using only 'low level,' easy-to-extract features such as the color histogram for each frame. Color histograms simply reveal the number of pixels in a frame that contain red, green, or blue, and frames with similar histogram profiles likely belong to the same class. They employed an unsupervised algorithm to extract these features and detect cricket events, and then trained a support vector machine to label clips as 'highlight' or 'non-highlight.' While this approach does not provide a more detailed understanding of events included in the summarized video, it presents a simple and lightweight highlights generation option with an overall out-of-sample accuracy of 87.9%.

Deep Learning

With the recent rise in popularity of neural network–based machine learning, deep learning frameworks have also been used to generate cricket highlights. Ravi et al.'s (2018) proposed a method to generate highlights by classifying the poses of umpires, as umpires make different hand gestures based on their ruling of the play. Ravi et al. focused on three play types: six runs; no-balls and wide balls, which are both illegal deliveries; and wickets. They employed two pretrained convolutional neural networks (CNNs) to extract umpire pose features from cricket footage, then used a linear support vector machine classifier to categorize and label umpire poses. With the use of CNNs, they achieved a remarkable 96.15% out-of-sample accuracy, showcasing the power of deep learning for video summarization.

Shingrakhia and Patel (2020) followed up on Ravi et al.'s (2018) usage of CNNs and developed a hybrid deep neural network (DNN) enhanced with a technique known as emperor penguin optimization (EPO). EPO is a biologically inspired optimization algorithm that mimics the huddling behavior of penguins (Dhiman & Kumar, 2018). Shingrakhia and Patel used EPO to determine the weights of their DNN, and then extracted exciting clips from cricket footage and automatically labeled them to generate a finished highlight. Their EPO-enhanced DNN was able to achieve an out-of-sample accuracy of 93.71%, further illustrating the potential of deep learning for cricket highlights generation. In the future, it is likely that neural network-based approaches will become the norm for automatically generating highlights from cricket footage.

Advanced Cricket Analytics: Tools for Decision-Making

For all members of a cricket organization, such as players, coaches, and management, data analytics tools offer a powerful avenue to improve and optimize gameplay. In particular, recurring problems in cricket such as ranking players, which involves synthesizing a variety of measured statistics, and team selection, which involves choosing an optimal subset of players from an organization's roster, have been tackled with data science.

Delivery and Strike Classification

During a cricket match, there is great diversity in the type of deliveries that bowlers throw and the type of hits that batters execute. Some common bowler delivery types include googlies, in which a spin delivery bounces opposite to the expected direction; yorkers, in which a fast delivery lands near a batsman's feet; and bouncers, in which a fast delivery is bowled short so that it reaches the batsman at head's height. In addition, bowlers can illegally deliver either wide balls, in which the ball is out of reach or behind the batsman, or no-balls, in which the bowler is too close to the batsman or the delivery reaches the batsman above waist height without having bounced. Classifying these illegal deliveries has been of interest within the cricket community to develop tools for automated umpiring. To that end, early work with ball tracking in augmented reality focused on classifying no-balls (Batra et al., 2014), but more recent work has shifted to broadly classifying deliveries either by player or grip using CNNs, which offer a more detailed picture of bowling strategy for organizations, broadcasters, and fans alike (Al Islam et al., 2019; Kumar et al., 2019; Rahman et al., 2021).

On the other side of a delivery, batter outcomes have typically been classified by the batter's motion. Three common motions are drives, in which batters swing vertically and hit the ball along the ground; sweeps, in which batters swing in a horizontal arc and catch the ball just as it bounces; and cuts, in which batters angle the bat to send the ball behind them. A variety of shot types in a batsman's repertoire allow them to find openings in the fielding team's position and score runs. A common approach for classifying individual shots has used multiple camera angles to track the outcome of each shot (Karmaker et al., 2015), but much of this data is only available to broadcasters. As a result, there has been recent interest in classifying batter outcomes in a more accessible manner. Some early approaches used motion estimation or wearable technology for different shots (Khan et al., 2017). Like bowling, however, these approaches have mostly been made obsolete with CNNs, particularly in broadcasted cricket matches (Foysal et al., 2019; Harun-ur-Rashid et al., 2018; Khan et al., 2018; Semwal et al., 2018; Sen et al., 2021). The most recent work at the time of publication, CricShotClassify, attains a 93% out-of-sample classification accuracy of batter outcomes.

Score and Match Prediction

Perhaps the most famous application of statistical inference to cricket is the 'delay prediction' calculation known as the Duckworth-Lewis method (Duckworth & Lewis, 1998, 2004). The Duckworth-Lewis method is typically employed due to inclement weather in limited-overs cricket, which shortens the second batting team's innings. This approach uses this team's remaining overs and wickets to predict an adjusted target score that it must surpass to win the game, instead of the original run target set by the team that batted first. The Duckworth-Lewis method was first introduced in 1988 and has since seen widespread adoption within the cricket industry. Indeed, the ICC now uses a slightly modified version of the Duckworth-Lewis method known as the Duckworth-Lewis-Stern (DLS) method as its official delay prediction tool (Stern, 2016). Using data accumulated since its adoption, some researchers have suggested modifications to the current DLS method to improve prediction and remove bias that they argue is inherent to the approach (Amjad, 2018; Singh & Adhikari, 2015). While these alterations can be simulated and applied retroactively to previous games, there has been no sufficient empirical evidence that demonstrates they perform better than the status quo, so it is unlikely that the DLS method will be replaced in the near future (McHale & Asif, 2013).

Other research has focused on predicting the outcomes of matches, which has potential importance in team selection for an organization and in sports betting for fans. Previous research has suggested that factors such as the outcome of the coin toss that determines which team bats first, home field advantage, and the time of the match (i.e., day versus night) influence match outcomes (Akhtar & Scarf, 2012; Clarke & Allsopp, 2001; Khan & Shah, 2015; Saikia & Bhattacharjee, 2010). A plethora of studies in the last several years have applied traditional machine learning approaches such as *k*-nearest neighbors, random forests, and logistic regression to predict match outcomes in a variety of formats at the professional level Ahmed et al. (2013)Jayalath, 2018;

Kapadiya et al., 2020; Pathak & Wadhwa, 2016). Other researchers have focused on modeling the performance of individual players to predict match outcomes (Jhanwar & Pudi, 2016; Swartz et al., 2009); however, these models require a significant amount of data, and have only been applied to one-day limited-overs matches thus far.

Evaluating Player Performance

Measuring player performance is a necessary mode of feedback for players and vital for team selection for organizations. For batsmen, the batting average has been an important historical device for quantifying performance, with early work focused on including not-out scores (Damodaran, 2006; Wood, 1945). Since then, several researchers have attempted to diversify performance metrics by introducing new statistics like batting performance or methods like neural networks, HMMs, and Bayesian approaches (Amin & Sharma, 2014; Beaudoin & Swartz, 2003; Iyer & Sharda, 2009; Koulis et al., 2014; Lemmer, 2004; Stevenson and Brewer (2017), (Stevenson & Brewer, 2021). For example, Stevenson and Brewer (2017) have proposed a Bayesian hierarchical model that measures the quality of a batsman by estimating a batsman's initial batting ability, peak batting ability, and the time required to achieve peak batting ability during an inning. The pair later extended the model by introducing Gaussian processes to capture fluctuations over a player's career and parameters to account for match-specific conditions (Stevenson & Brewer, 2021). Historically, bowler performance has received less attention. The combined bowling rate, built on several bowling statistics such as average runs conceded and average strike rate, remains an important metric in use (Adhikari et al., 2017; Lemmer, 2002). Recent work focusing on Test cricket has attempted to put batsmen and bowlers on a common scale for performance comparison (Akhtar et al., 2015).

Team Selection

For international cricket matches, a critical decision that each team must make is the lineup of players that they send to play, which can be particularly difficult for countries with a large pool of high-caliber players. A variety of optimization techniques have been applied to this problem Ahmed et al. (2013)Gerber & Sharp, 2006; Kamble et al., 2011; Lemmer (2013). The integer programming method built by Lemmer (2013) and the multi-objective algorithm proposed by Ahmed et al. (2013) are especially exciting in that they require inputs like batting and bowling metrics, emphasize interpretability for coaching staff, and are near-ready to be applied in practice. Some recent work has focused on selecting teams by considering roles outside of just batsmen and bowlers, such as captains, wicketkeepers, and batting partnerships (Adhikari et al., 2020; Bhattacharjee et al., 2018; Bhattacharjee & Saikia, 2016), while other work has considered the role of age in player performance (Hazra & Biswas, 2018; Jamil et al., 2021; Saikia et al., 2019). Team selection is further complicated in international leagues like the Indian Premier League, in which teams must also take into account a player's current valuation. Although these approaches broadly improve aspects of the team selection process, they may not necessarily yield a team that is optimally prepared to face an arbitrary opposing team. In the future, it is likely that decision-making algorithms in cricket will factor in data about the opposing team to generate more appropriate player lineups.

Conclusion

Though the use of data analytics in cricket is relatively recent, officials, teams, and players from all over the world are leveraging data-driven insights to improve gameplay. Umpires now regularly make use of the Decision Review System, which combines slow motion video replays with ball-tracking technology and directional microphones to adjudicate whether a batsman is out (Shivakumar, 2018). Rohit Sharma, the current opening batsman and captain for the Mumbai Indians cricket team, has been an avid proponent of applying data science to cricket. “[When] I’m on the field, those analytics and data given helps me… to make my decisions,” Sharma said (Mumbai Indians, 2020). Improvements on the fan side, on the other hand, serve to provide a more entertaining experience for viewers. In 2015, IBM released a popular #ScoreWithData campaign, in which they scanned Twitter to reveal which players and umpires were fan favorites during the 2015 World Cup (IBM Research Editorial Staff, 2015). In 2021, Cricket Australia, the governing body for the game in Australia, signed a first-of-its-kind partnership with TEG, a data analytics company focused on optimizing fan engagement ("Cricket Australia & TEG's Ovation in Ground-breaking Data Partnership," 2021). It is clear that the data science revolution in cricket is only beginning, and it will be exciting to see how the game evolves in the coming years.

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