A Thorough Survey for Cricket Shot Analysis Using Deep Learning

Atharv Pushkraj Nirgude[1] Rohit Dinesh Sonone[2] Sahil Vikram Sonawane[3] Rushikesh Sham Ahire[4] Prof. Balaji Bodkhe[5]
[1,2,3,4,5]Department of Computer Engineering
[1,2,3,4,5]MESCOE, Pune, India

Abstract— there has been increased attention and popularity of various sports in the recent years. The lack of any sporting event in the midst of the recent pandemic had also left a large number of individuals craving to watch some sport being played. One of the majorly followed sport in India is easily cricket with millions of fans that follow the game religiously. The fans are very much into the game and perform in-depth analysis of the various players and their performances especially their shot selection. With the rise of the fantasy leagues and other similar applications, there is an increased interest in evaluation of the players that are performing better to help choose them in their teams. The manual process of batter shot identification is one of the most time consuming and highly laborious process which can benefit by some kind of automation. Therefore, this survey article analyzes the past works on cricket shot analysis which has been useful in determining our approach for the same using image processing implementations.

Keywords: Image Normalization, Convolutional Neural Networks

I. INTRODUCTION

In India, cricket is perhaps the most prominent game. It is played between two sides, each of which has 11 participants. Each group seeks to score some runs, with the winning team being those with the maximum runs. The International Cricket Council recognizes three types of cricket, depending upon that game's runtime. Test cricket, which has unlimited deliveries, and One Day International (ODI) as well as Twenty-20 (T20) cricket, all of which have restricted overs. Another of the reasons that ODI has been the most prevalent type of sport is that it provides for a day-night structure as opposed to the traditional day-only version. The T20 format is also gaining a lot of popularity since the game can be completed quickly, which appeals to a lot of people who are too busy to watch a test match or even an ODI for long periods of time.

In Cricket, outcome assessment of a specific game (individual player performance and form) would be highly valuable well before the game is scheduled. If the assessment focuses on the competence of the players, a team might be matched up against a certain squad in such a fashion that the matchup results in win. There are several elements that may affect the effectiveness of a Game of cricket, including who ends up winning the toss, inclement weather, ground conditions, and whether or not the game is hosted in a team's home region. Aside from these external components, the competence of the victorious players on the team is the most important internal component. Each player's performance may be considered largely on how well he performed in previous matches, such as his average batting performance, the number of wickets he took, the number of catches he made, and so on.

Cricket is amongst the most entertaining sporting events; batting refers to the capability to smash a cricket ball using a cricket bat, and there are several types of cricket shots. Batters must adapt to varied circumstances when competing on distinct cricket fields, spread across different nations. As a result, top-level batters will also have fast conditioned response, outstanding decision-making process, and be brilliant decision - makers, in addition to possessing diverse physical striking capabilities. The use of machine learning and computer vision techniques in cricket for various analyses is currently a developing field. A variety of technologies are utilized in cricket for visualization and instruction. Recent studies have not shown sufficient results in terms of identifying gunfire.

Cricket matches contain a lot of interesting substance as well as a lot of economic potential. Because cricket is so popular throughout the world and has such a large audience, automated cricket video interpretation has gotten a lot of interest. Cricket is contested in a variety of different formats and follows a set of complicated regulations. Automatically assessing batters strokes from cricket match recordings is fundamentally challenging because to this complication. In terms of appearance, cricket matches have a lot of unnecessary camera shots. After removing the repeated sequences, even the selections may lack certain critical key occurrences, causing the viewers' attention to diminish. A cricket match's significant events include the boundaries, wickets, leg before wicket (lbw), umpire signals, celebrations, and replays. Automatically recognizing the shots executed is tough because even a simplified version must assess the batter's performances.

Cricket matches are often long, therefore there is a lot of multimedia material to broadcast. The whole cricket match is captured on camera, along with the batter's shots as well as other occurrences such as the audience and umpire signals. We are concerned in the batter's shot selection because viewers prefer to browse through the visual data and quickly discover the most relevant match events. Furthermore, processing, transmitting, and storing such large amounts of data is complex. Effective ways to browse those items and identify the shots played are challenging tasks in this regard.

This literature survey paper segregates the section 2 for the evaluation of the past work in the configuration of a literature survey, and finally, section 3 provides the conclusion and the future work.

II. RELATED WORKS

D. Karmaker et al. [1] proposed a technique for detecting specific cricket shots that incorporated numerous vision-based tracking technologies and their broad and consistent implementation. The authors used the MACH filter in their method and linked the test video with the MACH train set. After determining the greatest correlation criterion, they define several shots. The authors obtained the sum of motion vector findings from the optical flow study, which corresponds to the angle ranges for each of the angle classes. After determining the greatest correlation criterion, they define several shots.

A. Semwal et al. provide an innovative technique for detecting diverse strokes in the realm of cricket. The proposed system uses a pre-trained convolutional neural network to extract representations from the model's three auxiliary components. The model outperformed all previously employed state-of-the-art descriptors and classifiers, with promising detection accuracy. The authors included a new data set of 429 movies for 6 different types of cricket shots [2]. A more improved model, capable of precisely detecting the competence, might be extremely useful for professional sports training institutes. Cricket shot identification algorithms can be used for visualization and coaching, and a highly evolved model will find use in automatic commentary systems.

The identification and extraction of events and replays in cricket video have been accomplished by Punith Kumar M B. Color histogram characteristics have been frequently employed in shot detection applications. The most basic approach to using the color histogram technique is to determine the mean value of the RGB histogram for each frame and group similar frames together to detect a shot. The RGB histogram means were employed in the presented strategy to categories the pitch shots. BGM methods are employed to obtain replay shots in this case [3]. The player's motion is examined and identified using the Kalman filter, which is used to estimate the state of a linear system where the state is considered to be Gaussian distributed. The Kalman filter is a type of recursive predictive filter that employs state-space concepts and recursive algorithms. The state of a dynamic system is estimated. This dynamic system may be disrupted by noise, which is commonly believed to be white noise.

R. Roopchand et al. [4] developed a novel approach for cricket shot recognition based on bat detection and tracking, followed by cross-correlation with a training data-set with test video, an average positional inaccuracy rate of 5% was attained, along with an average bat identification rate of 85%. These approaches demonstrated the ability to obtain bat positioning data that is absent in previous cricket methodologies. While the findings for bat identification and tracking were gradually improved and used in the final implementation, shot recognition might be improved further by fine-tuning the cross-correlation values and time restrictions.

S. V. Ananth et al. intend to employ accelerometers to measure the strokes of players while they are playing. The kinematics chain pattern and accurate angular and translational motions of the player's knee, waist, and wrist, which are crucial for maximizing ball velocity upon impact, will be analyzed [5]. Thus, the system and methodology will be concerned with the building of a system that assists coaches and players in analyzing and studying their game. The authors are employing Inertia Measurement Units (IMU) as sensors and positioning them at various locations of a cricket/tennis player's body to determine a player's orientation for related strokes/actions played/performed. The technique of various players may be compared using data analysis, and the best potential approach for the stroke can be offered.

Sen, A et al. suggested a hybrid neural network architecture that correctly categorized ten distinct cricket batting swings from a video using publically accessible data sources Due to the lack of a publicly available dataset, the authors built their batting-shot dataset with varying durations, inconsistent lighting conditions, and overlapping sequences. The constructed dataset, to the best of their knowledge, includes the ten most distinctive batting shots. They want to make their dataset public after expanding it with more relevant films to perform more tests and enhance accuracy [6]. Experiment findings showed that when large amounts of data are unavailable, employing a pre-trained model is preferable. Transferring learning from a pre-trained model outperformed the other models after combining with GRU anytime the model was permitted to adjust its weight based on our dataset.

A novel technique for identifying distinct types of delivery in cricket using offline real-time footage of cricket bowling was presented by R. Rahman et al. A novel deep CNN model that was employed as a preliminary model to train the dataset demonstrated excellent accuracy when compared to various existing pre-trained transfer learning models. In addition, a completely new dataset including over 5000 photos classified into 13 different deliveries in cricket bowling was presented throughout this research [7]. This study is anticipated to be highly valuable for cricket players and coaches to train using video analysis, as well as for TV broadcasters of live cricket matches to include a new technology into their live broadcast. Finally, this study is intended to inspire academics to use deep learning to investigate numerous sports-related actions and activities.

By using the CNN model, Foysal et al. propose a cricket shot categorization strategy. Three convolution layers, three max polling layers, four dropout layers, one flatten layer, and two dense layers were employed in this research [8]. Dropout layers are used to reduce overfitting. The outcome authors discovered is quite encouraging. They hope that this technology will be evolved into a practical application for the benefit of cricket in the future. It would also be beneficial to the coaching system in terms of improving bowling and batting skills.

To extract key-frames from cricket match footage, S. H. Emon et al. propose a Deep Cricket Summarization Network (DCSN). They use the supervision signal and the diversity representativeness incentive to train the summarization network. They employ a near-optimal approach with dynamic programming to construct a summary based on the network's forecast. The authors do both objective and subjective analyses to evaluate their suggested technique. CricSum, a novel dataset, was created to quickly test the summarization network. Experiments with several variations of the proposed model on the CricSum dataset illustrate the efficacy of the technique. Furthermore, the subjective analysis yields a reasonable Mean Opinion Score (MOS), indicating that the presented approach is effective at collecting semantic information about cricket matches [9].

Using transfer learning, M. N. Al Islam et al. present a CNN model that can recognize distinct cricket bowlers based on their bowling movements. As a pre-trained transfer learning model, authors employed VGGl6 [10]. They took away its output layer and replaced it with a few thick layers. The authors produced their dataset and used it to train the machine to recognize 18 distinct cricket bowlers from seven different cricket-playing countries. With an average set accuracy of 93.3 percent and an Fl score of 93.2 percent, the presented model has done admirably.

Dixit Kalpit shows that employing a pre-trained VGG16Net to train a Long-Term Recurrent Convolutional Network may get excellent results on the job of identifying outcomes from cricket films [11]. He also compares the LRCN design to a single frame-based architecture, demonstrating that even the latter is a viable solution to this problem. On the validation set for this problem, the presented framework models can obtain an accuracy of around 80 %.

P. Shukla et al. [12] present an innovative technique for generating cricket highlights automatically. The four significant events in a cricket match, namely wickets, boundaries, sixes, and milestones, are extracted using event-driven features, while the remaining essential events are recognized using enthusiasm characteristics. OCR, playfield situations, and replays are used in event-driven strategies, whereas audio-based classifiers and replays are used in excitement-based tactics to underline the significance of an occurrence in a cricket match.

S. Manivannan et al. offer two innovative ways for forecasting the outcome of a Cricket match even before the match is planned, one based on Feature Encoding and the other based on CNN [13]. The ideas they provide are based on the players' previous performances in each squad. In their first method, authors assume that players are divided into distinct categories, and model each team as a collection of player-category connections, which are then used to train a linear SVM classifier on. The second method is based on a shallow CNN that is trained end-to-end to extract discriminative features and create a classifier to predict which side will win a specific match.

I. Bandara provides an innovative method for classifying cricket batting strokes [14]. He built a feature space consisting of spatiotemporal time series derived from produced stick figure video overlays to categories forward and rear foot strokes. Long Short Term Memory (LSTM) and Bidirectional LSTM networks were used to classify the data. For a dataset constructed from publicly available videos, both LSTM models correctly identified all of the movies from the testing split. The proposed method has the potential to improve coaching systems and the cricket viewing experience while also contributing to sports analytics.

NetClips, an AI-assisted tool for broadcast creation, was presented by M. Izadi et al.. NetClips automates correct tagging by identifying players and detecting game events. NetClips can annotate tens of thousands of videos provided by broadcasters. The authors intend to create a search capability in NetClips that will allow them to quickly access any needed video clips during or after production. NetClips is used in a wide range of entertainment enterprises, as well as sports, where it has the most impact. The authors investigated deep-learning-based architectures for detecting three significant events in broadcast recordings capturing the professional sport of cricket [15]. For extracting temporal characteristics, they used pre-trained convolutional neural networks and looked into using ensemble architecture to combine the separate networks. They used a huge dataset of a broadcast video from international cricket matches to test the capabilities of the suggested architectures.

Sayan Tapadar [15] present an analytical approach for optimizing collision identification using SVM While evaluating the collision recognition, researchers discovered that the alert was frequently activated often, which could be difficult for motorcyclists to react to it while operating the motorcycle. As demonstrated repeatedly, if the alert sounds and the motorcyclist presses the button, the gadget disregards the observation and does nothing. If the trigger is not pressed, the gadget thinks it is a genuine mishap and respond appropriately.

III. Conclusion and Future Scope

This survey paper evaluates the related works for the purpose of achieving the effective and useful realization of the cricket shot analysis of the batter using deep learning approaches to approach our methodology. Cricket is arguably one of the most popular sports in India, with massive followings who watch the games obsessively. The supporters are engrossed in the game and conduct in-depth analyses of the different players and their accomplishments, particularly their shot selection. With the growth of fantasy football leagues and other similar services, there is a renewed interest in evaluating individuals who are playing well so that they may be selected for their teams. The manual means of determining batter shots is among the most time-consuming and labor-intensive processes that might benefit from automation. As a result, this survey paper examines previous research on cricket shot assessment, which has proven to be valuable in deciding our approach to the problem utilizing deep learning approaches which will be elaborated in the upcoming editions of this research article.

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