A Survey: Intelligent Stroke Detection Using Convolutional Neural Network

Pradip Borade[1], Mangesh Bodke[2], Prateek Chakranarayan[3], Laxmi Borse[4], Prof. Smita Mulhar[5]
[1,2,3,4] *Smt.Kashibai Navale College of Engineering*
[5]*Prof. Smt.Kashibai Navale College of Engineering*

Abstract: Cricket is one of the most popular sports around the world. especially in the Indian subcontinent which has great cultural significance With the rapid advancement of technology Integrating cutting-edge tools such as computer vision and machine learning It has increased the accuracy and analysis of game data. In this paper, we propose a new approach for cricket ball recognition using artificial neural networks. Convolutional (CNN) It showcases the potential of deep learning to provide more accurate insights into cricket.

Keywords: CNN, Deep Learning, Cricket, Shot Detection, Machine Learning

1. INTRODUCTION

In the game of cricket, the analysis of player actions, including batting techniques and shots, is crucial for understanding player performance, strategizing gameplay, and improving training sessions. Traditionally, cricket action analysis relied heavily on manual observation, which is time-consuming and often subject to observer bias. However, with advancements in artificial intelligence (AI) and deep learning, sports analytics has entered a new era where automated action detection, including shot classification in cricket, can provide insights far faster and with greater precision than traditional methods.

Deep learning algorithms, particularly Convolutional Neural Networks (CNNs), have emerged as powerful tools for image recognition tasks, enabling systems to automatically learn relevant features from visual data. In cricket, these networks can be trained to identify and classify different types of shots such as drives, hooks, cuts, and sweeps. This process requires input from video feeds, where each frame is processed to capture unique patterns associated with each shot type.

This paper provides a comprehensive survey of the application of CNNs in cricket shot detection, evaluating methodologies, model architectures, datasets, challenges, and the potential for future developments. Our survey aims to consolidate information on the state-of-the-art approaches to cricket shot recognition using CNNs and hybrid models, detailing how they can facilitate automated analytics in cricket.

2. LITERATURE REVIEW

2.1. An Interactive Approach To Identify Cricket Shots Through Deep Learning Mechanism In recent years, numerous sports have received significant attention and appeal. In the height of the current epidemic, the unavailability of any athletic events had left a significant number of people yearning to observe some game being played. Cricket is arguably the most popular sport in India, with millions of followers who watch the games obsessively. Fans are enthralled by the game and conduct in-depth analyses of the individual players and their abilities, particularly their shot choices. With the growth of fantasy leagues as well as other similar services, there is a growing interest in evaluating individuals who are playing well so that they may be selected for their teams. The manual procedure of batter shot recognition is amongst the most time-consuming and labor-intensive processes that might be automated. As a result, this study provides a successful cricket shot assessment approach that makes use of deep learning in the form of Convolutional Neural Networks to fulfil its objective.

2.2. Applications of Machine Learning in cricket: A systematic review Cricket has become a famous team game around the globe, and it is considered the world’s second most popular sport (Pathak and Wadhwa , 2016). The plethora of available cricket data and the development of Machine Learning (ML technology have created a massive demand for cricket data analytics . The applications of ML in the cricket domain have increased dramatically during the last two decades. This study conducts a systematic review of the published research work during the last two decades (2001–2021) on the applications of ML in cricket

2.3. Cricket Video Highlight Generation Methods: A Review The key events extraction from a video for the best representation of its contents is known as video summarization. In this study, the game of cricket is specifically considered for extracting important events such as boundaries, sixes and wickets. The cricket video highlights generation frameworks require extensive key event identification. These key events can be identified by extracting the audio, visual and textual features from any cricket video.T he prediction accuracy of the cricket video summarization mainly depends on the game rules, player form, their skill, and different natural conditions. This paper provides a complete survey of latest research in cricket video summarization methods. It includes the quantitative evaluation of the outcomes of the existing frameworks. This extensive review highly recommended developing deep learning-assisted video summarization approaches for cricket video due to their more representative feature extraction and classification capability than the conventional edge, texture features, and classifiers. The scope of this analysis also includes future visions and research opportunities in cricket high light generation

2.4. A Predictable Deep Learning Inference Framework for IoT Devices: Deep learning is already transforming how computers integrated into IoT devices use sensor feeds to make wise decisions in the real world. For mobile and IoT devices with limited resources, there have been major efforts to design lightweight and extremely efficient deep learning inference techniques. Some approaches suggest a hardware-based accelerator, while others suggest employing various model compression techniques to reduce the amount of computing required for deep learning models [1]. Despite the fact that these initiatives have shown appreciable improvements in performance and efficiency, they are unaware of the Quality-of- Service (QoS) requirements of different IoT applications and as a result, exhibit unpredictable ”best-effort” performance in terms of inference latency, power consumption, resource usage, etc. Unpredictability in IoT devices with temporal constraints may have negative consequences, including.

2.5. Cognitive foundation of knowledge science and deep knowledge learning by cognitive robots: The comprehension of natural intelligence and the development of appropriate mathematical tools for rigorously modelling the brain in forms that are machine comprehensible are deeply rooted in one another, according to recent basic studies. Learning is the cognitive process of acquiring knowledge and action. Object identification, cluster categorization, functional regression, behaviour production, and knowledge acquisition are the five categories that learning can be divided into. According to Wang’s most recent work in knowledge science, the fundamental unit of knowledge is a binary relation (bir), such as a bit for information and data. The field of cognitive machine learning has emerged in response to a basic problem with knowledge learning that is distinct from those presented by deep and recurrent neural network technologies.

3.USE OF DEEP LEARNING AND CNN

3.1 Overview of Deep Learning in Sports AnalyticsDeep learning has revolutionized sports analytics, allowing for real-time and automated processing of complex visual data. CNNs, which are specialized for spatial data recognition, excel in identifying unique patterns within images and are particularly suitable for detecting features such as players’ poses, movements, and actions. In cricket, deep learning approaches help detect various types of batting shots by learning from large datasets of annotated cricket footage. RNNs, which can capture temporal patterns in sequential data, have also been employed in conjunction with CNNs to enhance the detection accuracy of cricket shots by integrating time-series information.

3.2 CNN-only Approaches

Many early approaches to cricket shot detection utilized CNN architectures exclusively, focusing on the classification of individual frames. CNNs consist of convolutional and pooling layers that sequentially filter input data to capture hierarchical features, from simple edges in early layers to complex textures in later layers. CNNs work well for frame-based classification, allowing models to recognize static image patterns associated with each shot type.

For instance, Mahajan et al. (2024) employed a 2D CNN model to analyze individual frames from cricket videos, achieving high classification accuracy for certain shot types. However, CNN-only models are limited in handling dynamic sequences and may misclassify shots when differences between consecutive frames are subtle. This led to the development of hybrid models combining CNNs with RNNs for enhanced performance.

4. DATASETS FOR CRICKET SHOT DETECTION

4.1 Importance of Datasets

Datasets are critical for training and evaluating deep learning models. In cricket shot detection, datasets consist of video clips or images, annotated by shot type, angle, and context. The variety and quality of data directly affect the model's accuracy and ability to generalize.

4.2 Notable Cricket Shot Datasets

1. CricShot10: This dataset includes video clips of ten common cricket shot types (cover drive, hook, pull, etc.) under varied lighting and camera angles. This diversity makes it valuable for training robust models.
2. SNOW: Captures cricket action sequences from broadcast videos with basic shot types and is useful for both training and validation.
3. Custom Datasets: Many researchers build custom datasets from manually annotated cricket footage. These datasets cover specific aspects or customized shot categories tailored to research goals.

5. METHODOLOGIES FOR CRICKET SHOT DETECTION

This section outlines common methodologies employed in cricket shot detection, from CNN-only models to more complex CNN-RNN hybrids and transfer learning strategies.

5.1 Convolutional Neural Network (CNN) Architecture

CNNs work by applying convolutional filters over input frames, detecting features such as edges, textures, and shapes. A typical CNN architecture includes multiple layers:

- Convolutional Layers: Learn filters that activate for relevant features, such as player outlines and bat movement.
- Pooling Layers: Reduce feature dimensionality, making computation faster.
- Fully Connected Layers: Output shot classification probabilities.

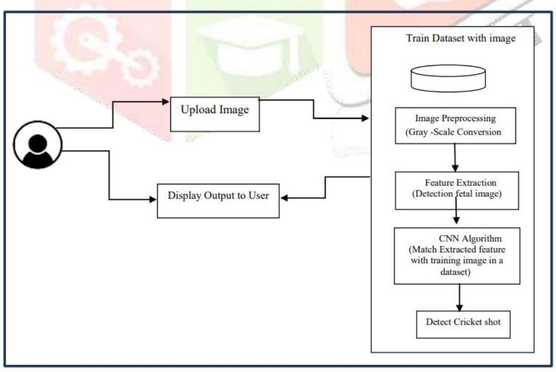

Figure 1: CNN Architecture

1. Data Collection: Assemble a diverse dataset of cricket videos containing instances of various shot types, including drives, pulls, cuts, and sweeps. Annotate the dataset with ground truth labels indicating the start and end frames of each shot.

2. Data Preprocessing: Extract frames from the cricket videos and resize them to a consistent resolution to ensure uniformity in the input data. Normalize pixel values to bring them within a standard range (e.g., [0, 1]). Split the dataset into training and testing sets to evaluate the model's performance.

3. Frame Extraction and Temporal Segmentation: Divide the cricket videos into individual frames, capturing the temporal sequence of shots. Apply temporal segmentation to isolate individual shots, ensuring that each frame sequence corresponds to a specific shot instance.

4. Model Architecture: Design a 2D Convolutional Neural Network (CNN) architecture suitable for shot detection. Stack multiple convolutional layers with activation functions (e.g., ReLU) to capture hierarchical features from input frames. Integrate pooling layers to down sample the spatial dimensions and reduce computational load. Add fully connected layers at the end for final shot classification.

5. Input Representation: Configure the input layer to accept 2D frames with color channels (RGB). Adjust the input size to match the resolution of pre processed frames. Consider using transfer learning with pre-trained CNN models to leverage features learned from large-scale image datasets, adapting them for shot detection

6. Training: Utilize the annotated training dataset to train the 2D CNN model. Define appropriate loss functions, such as categorical cross-entropy, to measure the disparity between predicted and ground

truth labels. Optimize the model using back propagation and gradient descent algorithms. Regularize the model to prevent over fitting by employing techniques like dropout and batch normalization.

7. Hyperparameter Tuning: Fine-tune hyperparameters such as learning rate, batch size, and the number of filters in convolutional layers to optimize model performance. Utilize techniques like grid search or random search to find optimal hyperparameter combinations.

8. Evaluation: Evaluate the trained model on the testing dataset to assess its generalization performance. Use metrics such as accuracy, precision, recall, and F1 score to quantify the model's ability to detect cricket shots.

9. Post-processing: Implement post-processing techniques to refine shot boundaries and eliminate false positives. Apply smoothing algorithms or heuristic rules to ensure temporal coherence and consistency in shot detection

10. Interpretability and visualization: Incorporate techniques for visualizing the learned features in the convolutional layers to gain insights into what the model has learned. Generate heatmaps or attention maps to highlight regions in frames contributing to shot detection decisions. K. Deployment If applicable, optimize the model for real-time processing and deploy it in cricket analysis systems or broadcasting setups. This detailed methodology provides a step-by-step guide for implementing a 2D Convolutional Network in cricket shot detection, emphasizing data preparation, model architecture, training, evaluation, and post-processing for robust and accurate shot detection

5.2 CNN-RNN Hybrid Models

CNN-RNN models combine the strengths of both networks. CNNs process each frame individually, while RNNs use the sequence of frames to learn temporal patterns.

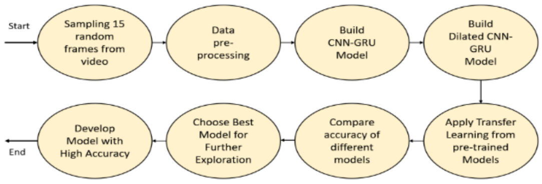

Figure 2: Diagram of CNN-RNN Model for Cricket Shot Detection

5.3 Transfer Learning in Cricket Analytics

Using pretrained models such as VGG16 or ResNet for cricket shot detection reduces training time and improves accuracy, particularly useful in data-scarce conditions.

6. EXPERIMENTAL EVALUATION AND RESULTS

Evaluation metrics such as accuracy, precision, recall, and F1-score are used to assess models:

- Accuracy: Measures correct predictions over total predictions.
- Precision and Recall: Precision shows model's exactness, recall its completeness.
- F1-Score: Harmonic mean of precision and recall, balancing both metrics.

Table 1: Model Performance Comparison

Model	Accuracy	Precision	Recall	F1 Score
CNN	83%	80%	82%	81%
CNN-GRU	91%	89%	90%	89.5%
VGG16 Transfer	87%	85%	86%	86%

7. TECHNICAL CHALLENGES

Challenges in cricket shot detection include:

- Video Quality Variability: Environmental lighting and video resolution impact model performance.
- Real-Time Constraints: Resource demands for real-time processing are high.
- Dataset Limitations: Limited large-scale annotated cricket datasets restrict model training.

8. APPLICATIONS

1. Broadcasting: Enables real-time shot detection and automated highlights.
2. Training and Coaching: Helps coaches analyze player techniques.
3. Fan Engagement: Improves the fan experience with detailed shot breakdowns.

9. FUTURE SCOPE

Future research can focus on:

- Real-Time Optimization: Developing faster models for live cricket analysis.
- Multimodal Integration: Combining video with audio and sensor data for improved context.
- Advanced Architectures: Explore EfficientNet or Transformer-based architectures for better performance.

10. CONCLUSION

This research paper depicts the process of a system for automated cricket shot analysis which attempts to utilize deep learning methods in order to get better results. The rational to any described method is to watch the advancing sport by the means of each recorded cricket shot by Convolutional Neural Networks which has been portrayed in the technique. To teach the CNN model, a database of many different shots made by the batsman is provided. The set of the data with pictures is, as the name implies, as data set image set cut, after which other image cut images into the cutting dataset image cutting, which is adjusted training taken into Collins cut cuts for cut Collins' training. After that, the model is already trained; the purpose of the model is to test pre processed and normalization input video without first showing it to the Collins detection. In order to assess the cricket shot performance, the outputs are presented in an orderly manner using a decision making method for quick and easy categorization of results.

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