Intelligent Stroke Detection Using Convolutional Neural Network

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***Abstract*—Cricket is one of the most viewed and played sports in the world. In Indian subcontinent cricket is viewed as a religion. In recent times there have been so much advancement in the technology related to sports field and cricket is not exception to that, from better cameras to edge detection accuracy is developing so fast. In this paper we have proposed method based on the Convolutional Neural Network to get better accuracy. Cricket, one of the most popular sports worldwide, especially in the Indian subcontinent, is not just a game but a passion followed by millions. The advent of advanced technologies in sports has transformed how the game is analysed, viewed, and understood. With the increasing availability of high-resolution cameras and sophisticated data analytics, there is a growing demand for automated systems that can provide in-depth insights into various aspects of the game. Among these, cricket shot detection has become an essential component in sports analytics, enabling coaches, analysts, and broadcasters to assess player performance more effectively.**

***Index Terms*—Cricket shots, Convolutional Neural Networks (CNN), Sports analytics, Deep learning Video analysis, Machine learning, and Image classification.**

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. Cricket Activity Detection 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. A Comprehensive Survey of Shot Detection and Performance Analysis: 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 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. Intelligent Stroke Detection Using Convolutional Neural Network: 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. Cricket Shot Detection Using Deep Learning: A Comprehensive Survey: 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. 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.

4.1 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.

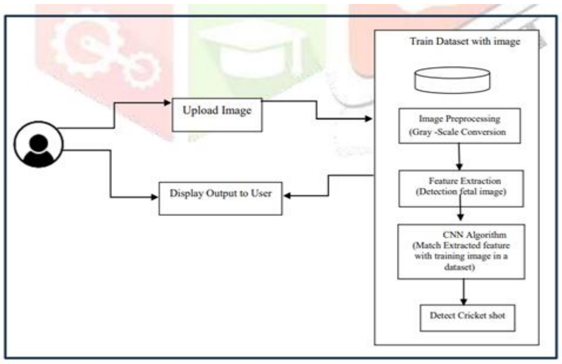

Figure 1: CNN Architecture

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 preprocessed 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

4.2 CNN Algorithm

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: Algorithm For CNN Model

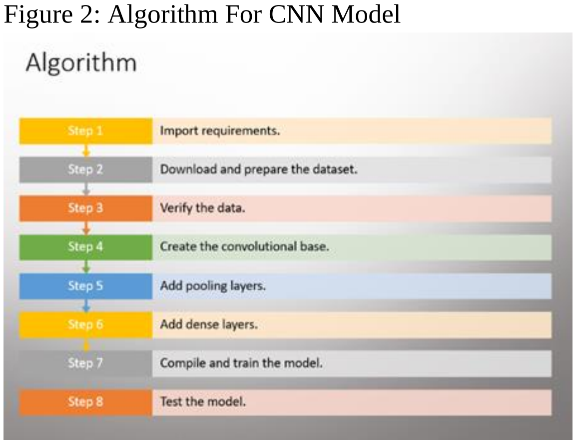

Figure 2 – CNN Algorithm

4.3 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.

5. EXPERIMENTAL EVALUATION AND RESULTS

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

Performance is evaluated using **Precision, Recall, F1-score,** and **Accuracy:**

$$\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{Total Predictions}}$$

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

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%

6. RESULTS

A 2D Convolutional Neural Network (CNN) trained for cricket shot detection yields a model capable of precisely identifying and categorizing diverse cricket shots within a given image set. The output is usually presented as predictions or labels assigned to each frame, indicating the specific shot type played by the batsman. The following aspects constitute the result of cricket shot detection in fig

Figure 3 – Result

Cricket shot predicted in the above result also showed execution time to show results. Firstly, pre-processing happens in the original image like original to grapy and binary and then testing, this method increases accuracy of the model. Fig 4 elaborated graphical representation of accuracy of system.

7. CONCLUSION

This cricket shot or Intelligent Stroke detection project, utilizing a dataset of 800 images, successfully demonstrates the efficacy of Convolutional Neural Networks (CNNs) in accurately classifying various cricket shot types within video frames. The primary objective was to precisely predict the shot type executed by a batsman, thereby enhancing analysis and automation in cricket performance evaluation. The project's output is typically presented as predictions or labels assigned to each video frame, indicating the specific shot type executed at that moment. These predictions serve as a fundamental component for automating shot recognition in real-time cricket analysis systems. In conclusion, the cricket shot detection project, utilizing a dataset of 800 images, has provided valuable classification of various cricket shots within a given set of images. The outcome is typically presented in the form of predictions or labels assigned to each frame, indicating the specific shot type played by the batsman. The cricket shot detection project, utilizing a dataset of 800 images, has provided valuable classification of various cricket shots within a given set of images. The outcome is typically presented in the form of predictions or labels assigned to each frame, indicating the specific shot type played by the batsman

REFERENCES

[1] A S. Rao, J. Gubbi, S. Marusic, and M. Palaniswami, "Crowd Event Detection on Optical Flow Manifolds," in IEEE Transactions on Cybernetics, vol. 46, no. 7, pp. 1524-1537, July 2024, DOI: 10.1109/TCYB.2015.2451136.

[2] D. Tang, "Hybridized Hierarchical Deep Convolutional Neural Network for Sports Rehabilitation Exercises," in IEEE Access, vol. 8, pp. 118969-118977, 2024, DOI: 10.1109/ACCESS.2020.3005189.

[3] Følstad, Asbjørn, and Marita Skjuve. "Chatbots for customer service: user experience and motivation." In Proceedings of the 1st International Conference on Conversational User Interfaces, pp. 1-9. 2023

[4] H. Ma and X. Pang, "Research and Analysis of Sports Medical Data Processing Algorithms Based on Deep Learning and Internet of Things," in IEEE Access, vol. 7, pp. 118839-118849, 2022, DOI: 10.1109/ACCESS.2019.2936945.

[5] Sen, A., Deb, K., Dhar, P.K., Koshiba, T., "CricShotClassify: An Approach to Classifying Batting Shots from Cricket Videos Using a Convolutional Neural Network and Gated Recurrent Unit. Sensors", 2021, 21, 2846. https://doi.org/10.3390/s21082846

[6] R. Rahman, M. A. Rahman, M. S. Islam, and M. Hasan, "DeepGrip: Cricket Bowling Delivery Detection with Superior CNN Architectures," 2021 6th International Conference on Inventive Computation Technologies (ICICT), 2021, pp. 630-636, DOI:10.1109/ICICT50816.2021.9358572

[7] S. H. Emon, A. H. M. Annur, A. H. Xian, K. M. Sultana, and S. M. Shahriar, "Automatic Video Summarization from Cricket Videos Using Deep Learning," 2020 23rd International Conference on Computer and Information Technology (ICCIT), 2020, pp. 1-6, DOI: 10.1109/ICCIT51783.2020.9392707.

[8] R. Ji, "Research on Basketball Shooting Action Based on Image Feature Extraction and Machine Learning," in IEEE Access, vol. 8, pp. 138743-138751, 2020, DOI:10.1109/ACCESS.2020.3012456

[9] M. Moness, S. K. Loutfy and M. A. Massoud, "Selecting Promising Junior Swimmers in Egypt Using Automated Biometric Algorithms of Image Processing and Fuzzy Concepts," in IEEE Access, vol. 9, pp. 89476-89496, 2021, DOI:10.1109/ACCESS.2021.3088409.

[10] J. Sevcık, V. Sm´ıdl, and F. Sroubek, "An Adaptive Correlated Image Prior for Image Restoration Problems," in IEEE Signal Processing Letters, vol. 25, no. 7, pp. 1024-1028, July 2020, DOI:10.1109/LSP.2018.283