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Research Article

Exploring Deep Learning in Cricket: A Shot Detection and Analyzing Techniques

[1]Nilesh P. Sable, [2]Vijay U. Rathod, [3]Rahul B. Mannade, [4]Kanchan Sitaram Pradhan, [5]Ravindra S. Tambe, [6]Rahul Ganpat Raut,

[1]Department of CSE (Artificial Intelligence), Bansilal Ramnath Agarwal Charitable Trust's, Vishwakarma Institute of Information Technology, Pune; drsablenilesh@gmail.com
[2]Department of CSE (Artificial Intelligence & Machine Learning), Bansilal Ramnath Agarwal Charitable Trust's, Vishwakarma Institute of Technology, Pune; vijay.rathod25bel@gmail.com
[3]Department of Information Technology, Government College of Engineering Aurangabad; mannade.rahul@gmail.com
[4]Department of Computer Engineering, MIT Academy of Engineering; kanchanpradhan2705@gmail.com
[5]Department of Computer Science & Design, Dr.Vithalrao Vikhe Patil College of Engineering, Ahmednagar; ravindra.tambe01@gmail.com
[6]Department of Information Technology; Dr.Vithalrao Vikhe Patil College of Engineering, Ahmednagar; braut_rahul@yahoo.co.in

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ABSTRACT

Using deep learning techniques, this research study offers a novel method for analyzing cricket shots. The goal of the project is to build a solid framework that can reliably classify and examine different kinds of cricket shots under various playing circumstances and player styles. The technique begins with gathering a large dataset of cricket shot films, which is then rigorously preprocessed to annotate different sorts of shots. The next step involves choosing and training a Convolutional Neural Network (CNN) or Recurrent Neural Network (RNN) model to identify and categorize cricket shots according to their visual attributes. The principal aims of this study are as follows: (1) Construct a deep learning model that can reliably categorize cricket strokes; (2) Assess the model's performance through extensive testing and contrast with conventional techniques and (3) Use deep learning techniques to improve your analysis of cricket shots. This research is important because it has the potential to transform cricket performance evaluation and sports analytics. This study intends to use deep learning techniques to offer more accurate and thorough insights into cricket shot execution, assisting players, coaches, and analysts in making strategic decisions and optimizing performance.

Keywords: Deep learning, sports analytics, Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and analysis of cricket shots.

1. INTRODUCTION

The use of advanced analytics and technical advancements in cricket, one of the most popular sports in the world, has increased significantly in recent years. Understanding and classifying various shot types is one of the many facets of cricket analysis that is essential to analyzing the details of player performance, strategy development, and general game dynamics. The accuracy and robustness of traditional shot categorization techniques may be compromised by their reliance on manual observation or oversimplified rule-based algorithms, particularly when handling the complexity and diversity of contemporary cricket shots [1, 2]. This project aims to improve cricket shot analysis by utilizing deep learning techniques as a solution to these problems.

Image identification, natural language processing, pattern recognition, and other domains have seen impressive results from deep learning, a branch of artificial intelligence that draws inspiration from the composition and operations of the human brain. This work intends to obtain more accurate and dependable shot classification by utilizing deep learning approaches to cricket shot analysis [3, 4]. This will yield important insights into player performance, strategy evaluation, and game dynamics. This project aims to create and assess a deep learning model that can correctly classify a wide variety of cricket shots. In order to accomplish this, a large collection of crickets shot films is gathered and annotated with various shot types, such as flick, lofted, defensive shot, square cut, late

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cut, cover drive, hook, straight drive, sweep, and pull. The dataset includes shots made by players with different styles and skill levels and under different playing conditions [5, 6].

The limitations associated with standard shot classification methods can potentially be overcome by utilizing Convolutional Neural Networks (CNNs), one of the deep learning approaches employed. CNNs are excellent at identifying hierarchical characteristics in visual data, which makes them suitable for jobs like classifying and recognizing images. This research aims to provide automated and accurate recognition and categorization of cricket shots by training a CNN model on the annotated dataset. This will allow for more thorough and analytical monitoring of player performance and game strategies. By demonstrating the effectiveness of deep learning approaches in cricket shot analysis, this study also aims to make a contribution to the larger area of sports analytics. It is anticipated that the results of this study would improve our knowledge of cricket dynamics and open doors for other sports disciplines to implement advanced analytics methods. In conclusion, by utilizing deep learning techniques, this research seeks to close the gap that exists between conventional shot categorization methods and the requirements of contemporary cricket analysis. This project aims to improve the accuracy, effectiveness, and breadth of cricket analysis for the benefit of players, coaches, analysts, and aficionados by offering a strong foundation for automated shot classification.

2. LITERATUTRE SURVEY

In paper [1], author presents a technique for cricket shot analysis using deep learning, particularly Convolutional Neural Networks (CNNs). It involves preprocessing and normalization of a dataset of cricket shot images, followed by training and testing using CNNs. The method demonstrates promising results, indicating its potential for further development and application in cricket analytics [7, 8].

Using CNN for spatial feature extraction and RNN (most especially, GRU) for temporal dependencies, the literature review emphasizes the effectiveness of CNN-RNN hybrid architectures for cricket batting-shot classification. Achieving increased accuracy through model refinement and ensemble approaches, utilizing transfer learning from pertained CNN models like VGG16, and creating custom models are important aspects to know [2, 9].

In order to identify cricket bowlers based on their bowling movements, the paper suggests a CNN-based approach that uses transfer learning. It achieves 93.3% accuracy on a test set and makes use of a customized dataset called "BowlersNet". Using CNN, transfer learning, VGG16, and cricket bowlers as keywords, it addresses the demand for automatic bowler identification in cricket broadcasts and advances sports computer vision research [3, 10].

With an accuracy of 92%, recall of 91%, and F1 score of 91% across a variety of cricket activities, this study presents an optimized deep learning model designed for cricket activity detection. It does this by utilizing a new CNN-LSTM architecture, which outperforms other recurrent neural network versions [4, 11].

This study analyses the amount of research on cricket analytics in great detail, with a particular emphasis on how IoT sensors and data analytics can be combined to create the timing index paradigm. This will improve player performance analysis and stroke play insights by using artificial intelligence techniques to improve accuracy and precision [5, 12].

The cricket shot recognition system presented in this paper uses a 2D CNN and achieves 91.5% accuracy in classifying different types of cricket shots. The study emphasizes real-time applications and performance enhancement by integrating deep learning techniques, convolutional neural networks, and image processing for automatic shot identification [6, 13].

The 13-layer Convolutional Neural Network "Shot-Net," which is presented in this research, is capable of categorizing six different types of cricket shots: Cut Shot, Cover Drive, Straight Drive, Pull Shot, Scoop Shot, and Leg Glance Shot. The model shows promise in cricket shot classification, with an average precision of 0.80, recall of 0.79, and F1-score of 0.79 on a test dataset with 840 images [7, 14].

Analyses of machine learning in cricket from 2001 to 2021 reveals a notable advancement in the use of methods like SVM, RF, and NB to forecast player performance, game outcomes, and batting styles. Accurate data selection, feature extraction, and resolving unequal study distribution—particularly in fielding—are among the challenges [8, 15].

With high accuracies of 89.74% for umpire/non-umpire detection, 83.33% for shot classification, and 80.51% for gesture detection, the paper introduces a CNN- based model for automated classification of umpire gestures and batsman shots in cricket. This provides up the opportunity for further research in automated cricket analysis and practical implementation [9].

The paper presents a deep learning-based multi-modal fusion model for efficient feature representations in cricket data analysis, achieving significant performance improvements over traditional methods. The literature survey highlights various approaches in cricket data analytics, including simulation, prediction models, and player performance evaluation, emphasizing the growing importance of data-driven insights in cricket [10].

3. PROPOSED METHODOLOGY

- **Workflow**

1. Data Preparation: Download and divide films of cricket shots into test, validation, and train sets.
2. Data Preprocessing: Resize, normalize, organize, and convert videos to frames.
3. Model Building: Select a model (such as Conv2Plus1D or Efficient Net), specify the architecture, and compile using the proper parameters.
4. Training: Utilize a validation set to monitor the model while it is trained, and take measures to avoid over fitting.
5. Evaluation: Use metrics like accuracy to evaluate the model's performance on the test set.
6. Visualization: For analysis, plot training curves and a confusion matrix.
7. Deployment: Use the model in an application or system, or save it for later use.
8. Iterative Improvement: Examine results, adjust model/hyper parameters, and continue.
9. Documentation: Record the complete procedure for sharing knowledge and using as a reference.

- **Dataset Collection**

Cricket enjoys a vast global fan base, leading to a substantial community of content creators and editors who regularly upload and edit cricket-related videos. Our dataset leverages this extensive online presence, comprising clips sourced from YouTube videos and various editor databases.

- **Primary Data Sources**

1. **YouTube Videos:** We collected cricket video clips from numerous YouTube channels. These channels include professional cricket broadcasters, fan compilations, and coaching tutorials. The selection criteria focused on the quality, relevance, and variety of the cricket shots featured in the videos.
2. **Editor Databases:** In addition to YouTube, we accessed databases maintained by cricket video editors. These databases include professionally edited footage and annotated clips that provide detailed breakdowns of different cricket shots.

- **Data Collection Process**

1 **Clip Extraction:** The video clips were extracted using a combination of automated tools and manual selection. Automated scripts identified relevant sections of videos based on metadata and visual content analysis, while manual verification ensured the accuracy and quality of the extracted clips.

2 **Annotation:** Each clip was meticulously annotated with the type of cricket shot it represented. The annotation process was conducted by cricket experts to ensure high precision in classifying the shots.

- **Dataset Scope and Characteristics**

For the early development phase, we focused on a curated selection of 10 distinct cricket shots. This decision was made to manage the complexity and ensure a high-quality dataset. The classes included in our dataset are:

  - Flick

- Lofted
- Late Cut
- Square Cut
- Cover Drive
- Hook
- Straight Drive
- Defense
- Sweep
- Pull Shot

- **Volume and Granularity:** The dataset comprises approximately 2000 video clips. Each cricket shot category contains a minimum of 160 videos, ensuring balanced representation across all classes.
- **Frame Rates:** The video clips in the dataset have varying frame rates, ranging from 30 to 120 frames per second (fps). This variation reflects the diversity of source material and helps in creating a robust dataset adaptable to different analysis requirements**.**

- **Data Quality and Reliability**

1. **Source Credibility:** The primary sources are reputable YouTube channels and professional editor databases, ensuring the authenticity and quality of the footage. Each clip was cross-referenced with multiple sources to verify the shot type and context.
2. **Validation:** The annotation process involved multiple rounds of verification by cricket analysts to minimize errors and ensure consistent labeling across the dataset.

- **Technologies Stack**

Tensorflow or Pytorch is used for developing deep learning models, OpenCV is used for video processing tasks, Keras is used to streamline the creation of neural networks, and Python is used for general development in the suggested technology stack for developing a cricket shot classification system. We will use transfer learning strategies in conjunction with machine learning models such as CNNs and RNNs. Databases or file storage will be used to store the data. Web development will use HTML, CSS, and JavaScript for the front end and frameworks like Flask or Django for the back end. Cloud platforms using Kubernetes for orchestration and Dockers for containerization will host the deployment. Jupiter Notebooks, Git for version control, and visualization frameworks for data analysis are some other tools.

4. IMPLEM/ENTATION

In the implementation of our (2+1) D convolutional neural network for video processing, we adhere to a standardized machine learning pipeline. This includes the sequential stages of Data Collection, Data Preprocessing, Exploratory Data Analysis (EDA), Model Selection, and Model Evaluation. Here's a detailed breakdown:

1. **Data Collection:** Given the relative scarcity ofreadily available video datasets compared to othermedia types like images, audio, and text, we embarked on creating our own dataset tailored to our specific needs. We extensively discuss our approach to dataset collection in Section 3.1 - Dataset Collection. The collected data is stored inan S3 bucket for remote access and management.
2. **Data Preprocessing:** Video data necessitates significant preprocessing before it's ready for model training or testing. Our preprocessing pipeline involves several crucial steps:

   2.1 **Reading Video Data:** We utilize the OpenCV library to read video data. The Video Capture routines facilitate file accessand conversion into tensor-like objects. Toensure data consistency, we resize videos and add additional padding frames.

2.2 **Converting to Fixed-Size Arrays of Images:** Models require data in a consistentshape, but raw video data often lacks uniformity. Thus, we transform the data into fixed-size arrays of images. Additionally, since OpenCV returns images in BGR format, we convert them tothe more commonly used RGB format.

2.3 **Converting into Inerrable Objects:** Given thepotentially large size of video data, loadingentire videos into memory is impractical. To address this, we convert the data into inerrable objects, allowing frames to be loaded and processed on-the-fly. Thisminimizes memory usage by loading only necessary data. We also organize the data into batches for computational and memory efficiency. Moreover, labels are one-hot encoded to facilitate model training.

3. **Exploratory Data Analysis (EDA):** EDA plays a pivotal role in understanding dataset characteristics and ensuring data quality. Visualization and analysis are crucial, especially for diverse datasets like ours. In our case, it's imperative to ensure that selected frames provide relevant information about the labels as shown in Figure 1.

Figure 1: Precision Cricket Shot

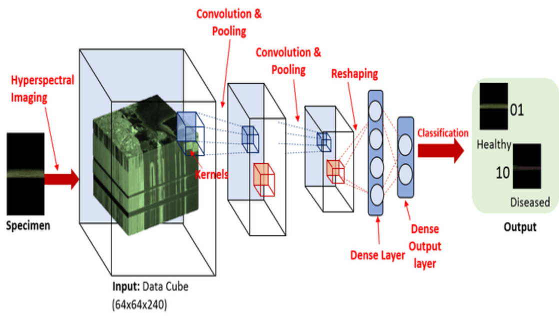

Figure 2: General CNNs Architecture [5]

4. **Model Selection:** While various models exist for video data processing, including 3D convolutional neural networks and different recurrent neural network (RNN) architectures, our research paper focuses primarily on (2+1) D convolutional neural networks. This choice is justified by: better documentation.

Suitability to our problem domain, specifically its capacity to effectively capture spatiotemporal features in video data.

5. **Model Architecture Summary:** We propose novel 2+1D convolutional neural network architecture for video processing tasks as shown in Figure 2. The model is designed to extract spatiotemporal features from video sequences and perform classification tasks. The architecture comprises several key components:

5.1 **Input Layer: -** Accepts video sequences with a shape of \`(None, 10, HEIGHT, WIDTH, 3)\`, where \`HEIGHT\` and \`WIDTH\` represent the spatial dimensions, and \`3\` denotes the threeRGB color channels.

5.2 **Conv2Plus1D Layer:** A specialized layerperforming spatiotemporal convolutionswith 16 filters of size `(3, 7, 7)` and ``'same'`` padding.

5.3 **Batch Normalization and ReLU Activation: -** Batch normalization is applied to normalize activations, followed by Rectified Linear Unit (ReLU) activation to introduce non-linearity.

5.4 **Resize Video Layers: -** Resizes the spatial dimensions of the video tensors, progressively reducing them by half after each residual block.

5.5 **Residual Blocks: -** Four residual blocks are stacked, each containing convolutional layers followed by batch normalization and ReLU activation. The numberof filters increases in each block, from 16 to 128.

5.6 **Global Average Pooling:** Reduces the spatial dimensions to 1x1 by taking the average over each feature map, capturing the global spatiotemporal patterns.

5.7 **Flatten Layer:** Flattens the 2+1D tensor into a 1D tensor to prepare for classification.

5.8 **Dense Layer:** A fully connected layer with 10 units for classification into 10 classes. Thisarchitecture is trained end-to-end using standard optimization techniques to minimize classification loss.

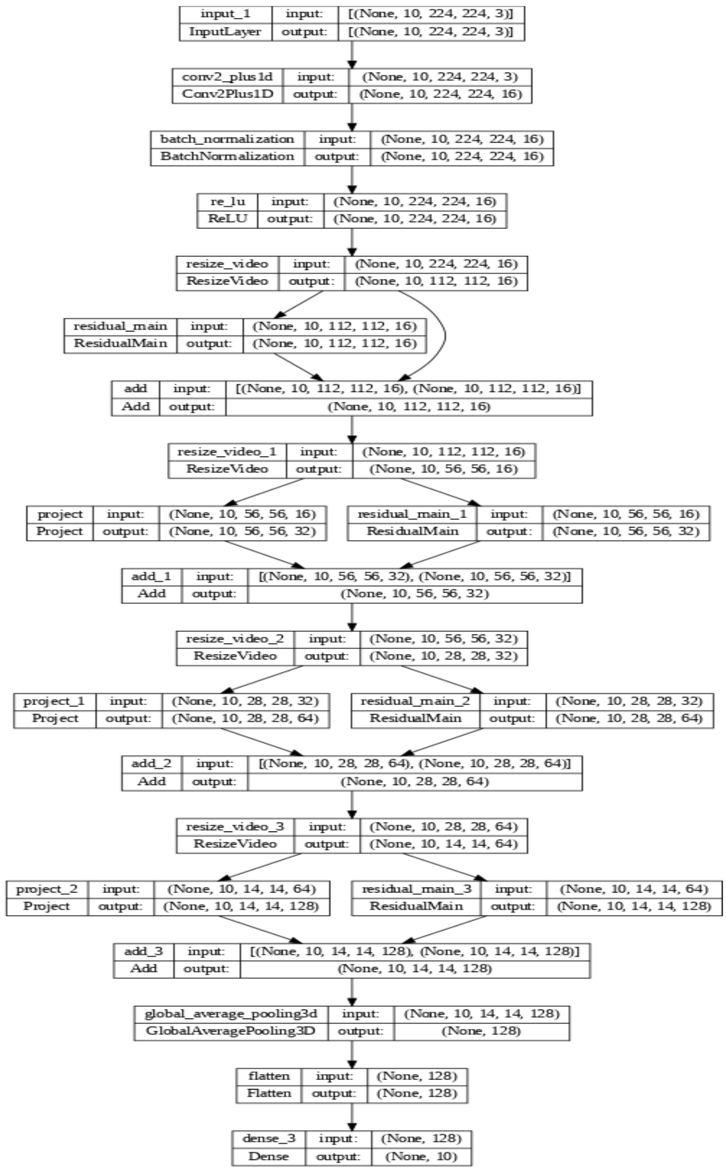

Figure 3: Deep Learning implementation Model

The proposed model demonstrates promising performance on various video classification benchmarks,showcasing its effectiveness in capturing both spatial andtemporal information in video data as shown in Figure 3.

5. RESULTS AND DISCUSSION

Our model achieved 55%+ validation accuracy after 50 epochs as shown in Figure 4. Enhancements such as expanding the dataset and refining the architecture could improve accuracy. Larger datasets provide richer examples for learning, while architectural adjustments, like adding layers, better handle complexity. Graphs tracking epochs versus loss and accuracyvisually represent the model's learning progress. Future improvements aim to enhance accuracy and effectiveness in classifying complex video datasets.

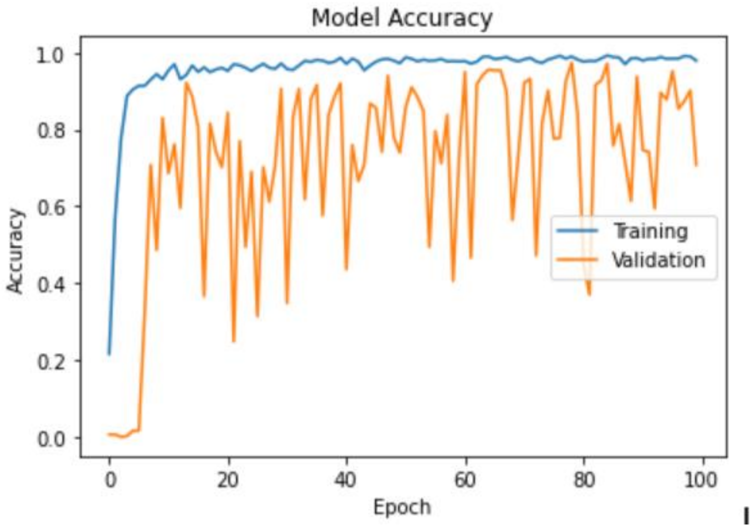

Figure 4: The validation accuracy after 50 epochs

6. CONCLUSION

In conclusion, creating a system for classifying cricket shots requires a thorough methodology that combines data collection, preprocessing, training models, assessment, and implementation. An effective and precise system can be developed by utilizing machine learning techniques, cloud services, web development frameworks, and technologies such as Python, OpenCV, Tensorflow, or Pytorch. The effective deployment of such a system creates opportunities for real-time decision-making and advanced analytics in cricket in addition to helping to understand player performance. This approach has the potential to have a big impact on cricket at many different levels, from coaching to professional match analysis, with continued improvement and modification.

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