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Detection of different Cricket Shots from Video Footage using Machine Learning

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***Abstract*—Detection and classification of cricket shots have turned out to be essential components of sports analytics in terms of giving insights into a player's performance and strategy. The present paper develops a robust framework that uses a hybrid CNN-LSTM architecture for the classification of cricket shots using advanced computer vision and deep learning techniques. Spatial features are extracted with the help of a ResNet50 backbone while temporal analysis is done with LSTM layers to give comprehensive processing to video sequences. Notable innovations include the use of dataset augmentation, balancing techniques, and early stopping to enhance the model's performance. Experimental results show moderate accuracy while pointing out the strengths and limitations of the proposed system. Results conclusively indicate that AI-based solutions to enhance the analytics of sports hold great promise for making value additions toward intelligent performance evaluation in cricket.**

***Index Terms*— Cricket Shot Detection, Computer Vision, Sports Analytics.**

I. INTRODUCTION

Recently, cutting-edge technologies such as artificial intelligence (AI) and computer vision have revolutionized sports analytics that give detailed insights into the performance of players and the dynamics of games. These technologies prove resourceful in the game of cricket that is one of the most popular sports worldwide. The most important part is shot detection which plays a key role in defining the techniques used by batsmen, their strategies as well as overall performance. This work presents a robust cricket shot detection system that would take video footage and recognize various shots like cover drives, pulls, sweeps, etc., and deduce important factors from the match associated with them. Cricket shot detection features advanced techniques in machine learning and computer vision for analyzing video streams. Techniques range from Convolutional Neural Networks (CNNs), responsible for extracting spatial features, Long Short-Term Memory (LSTM), useful for establishing temporal relationships to object detection algorithms such as YOLO (You Only Look Once), capturing both batsmen and the ball. Preprocessing, pose estimation, and optical flow analysis contribute to this accuracy. Sentiment analysis of the commentary data is added to our analysis with the, CNN to evaluate emotional tone and context of some crucial events in the match. In this way, the research proposes a hybrid framework for exhaustive cricket match analysis, enabling computer vision as a medium of shot detection to integrate with CNN and LSTM for Shot analysis. The system identifies and classifies shots in cricket while placing them into the games narrative by relating them to boundaries or even to wickets.

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II. Literature Review

In this section the comparative study of literature survey is shown in table 1.

TABLE I: COMPARATIVE STUDY OF LITERATURE

Paper	Focus	Key Techniques	Applications	Findings
M. N. Al Islam, T. B. Hassan and S. K. Khan [1]	A CNN-based approach to classify cricket bowlers based on their bowling	Computational modeling, Training, Predictive models, Feature extraction.	Automated video analysis, highlight generation	Progressed accuracy, especially in occlusions.
H. K. Aggarwal, K. Verma, and S. Singh.[2]	Cricket Video Shot Classification	CNNs, Transfer Learning	Detection of shot types, real-time classification	Promising consequences in shot classification, especially with great-tuning.
M.C. Kampffmeyer [3]	Multi-View CNN for Cricket Shot Detection	CNNs	Cricket performance evaluation, Coaching	High accuracy in shot detection, capability for real-world package.
S. Pandey, D. Choudhury, and M. K. Reddy[4]	End-to-End Deep Learning Models for Cricket Shot Recognition	Deep Learning	Cricket overall performance analysis, Commentary	Ability for enhancing accuracy and generalization with large datasets.
A. Khan, F. H. Nabila, M. Mohiuddin, M. Mollah, A. Alam and M. Tanzim Reza [5]	An Approach to Classify the Shot Selection by Batsmen	Deep learning, Image segmentation, Computational modelling, Neural networks, Computer architecture.	Cricket overall performance analysis, Coaching	High accuracy in classifying bowler sorts.
J. B. Fernandes, P. S. Ram, P. M. V. Yadav and K. P. Kumar [6]	Cricket Shot Detection using 2D CNN	Deep learning, Computer vision, Convolution, Computational modeling, Games, Control systems.	Video indexing, summarization	High accuracy (98.6%) in classifying pitch frames.
M. Jagadeesh, R. S and S. Y [7]	Cricket Shot Detection Using Deep Learning	Deep learning, Legged locomotion, Transfer learning, Hardware, Classification algorithms	Real-time decision making, automated commentary	High accuracy (98.20%) in classifying six major cricket activities.

Most of the research [8-10] in cricket shot analysis have been carried out using deep learning techniques, mainly CNNs. A few of those previous works have also already demonstrated their effectiveness in shot detection and classification with high accuracy. Here, [1] carried out his work based on transfer learning to achieve higher accuracy. Good accuracy was also achieved by Aggarwal et al. [2] through the integration of multimodal feature integration. Some notable breakthroughs are Kampffmeyer's [3] multi-view CNN approach and Pandey et al.'s [4] end-to-end deep learning models, which demonstrate promising real-world results. More recent work by Khan et al. [5] and Al Islam et al. [6] includes classification of bowlers with detailed performance assessment, and Fernandes et al. [7] along with Jagadeesh et al. obtained unbelievable accuracy rates of 98.6% and 98.20% respectively for their respective applications. These studies collectively make a good foundation for automated cricket analysis, yet a lot of improvements are still necessary in real-time processing, handling occlusion, and more robust models under a variety of playing conditions. Motivated by these results, the current study attempts to bridge the gaps while exploiting the proven success of CNN-based approaches in cricket shot analysis.

III. Methodology

Advanced preprocessing and hybrid deep learning techniques are applied to optimize shot classification accuracy for cricket shot detection. The flow of the adopted methodology is shown in Figure 1. The major steps involved are described below.

A. Data Collection and Preprocessing

For the video recordings of cricket, seven types of shots are specified, namely: cut, drive, pull, flick, slog, sweep, and misc. Frames in the videos have been extracted and resized to pixels of 50x50 units using OpenCV's Video Capture function. Such frames are normalized and converted to value ranges between 0 and 1. The rotation, horizontal flipping, zooming, and scaling techniques are done on the dataset. Here, the ImageDataGenerator of the TensorFlow library would be used.

B. Feature Extraction

The model applies a pretrained ResNet50 on ImageNet for spatial feature extraction. In order to ensure temporal coherence over video frames, this model is wrapped in a TimeDistributed layer.

C. Model Architecture

The hybrid CNN-LSTM model has three important components. One, it uses the base model ResNet50 for efficient spatial feature extraction from frames of the video. Two, the features are fed to a 512-unit LSTM layer that captures the sequences for the shots of cricket happening at any instance. Finally, the architecture employed is that of fully connected layers, concluded with a softmax layer for the categorization of input instances into one of seven types of cricket shots. Dropout layers are used for regularization to reduce overfitting and enhance generalization.

D. Data Set Balancing

The technique of resampling is used in class imbalances so that there is equal representation of all the shot types.

E. Training and Evaluation

Splitting this dataset into training (80%), and test subset (20%), the train_test_split function is used. In addition, the model uses the Adam optimizer, learning rate set to 0.0001, and categorical cross-entropy as loss function. Also, early stopping was implemented to prevent overfitting by monitoring the validations loss. In addition to that, accuracy, precision, recall, and F1 score were calculated for performance evaluation. It shows detailed analysis on loss/accuracy trends, confusion matrices, etc.

This methodology is based on spatial feature extraction from pre-trained CNNs, and temporal modelling from LSTMs with robust training strategies with data augmentation and class balancing. The inclusion of performance visualizations, such as learning curves and confusion matrices, makes sure that complete analysis and evaluation are done. This approach, therefore, makes real-time cricket shot detection feasible with improved accuracy and adaptability to class imbalances.

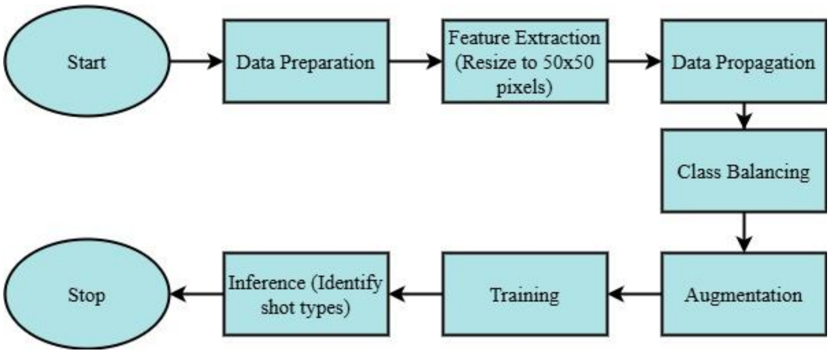

Figure 1. Flowchart of hybrid CNN-LSTM

IV. RESULTS ANALYSIS

This research presents the performance of the proposed hybrid CNN-LSTM model for the detection of cricket shots. Experimental evaluation of the model indicates moderate overall accuracy to be 50% with precision, recall, and F1-scores being marginally lagging. The system correctly classifies various cricket shot types while a few misclassifications still occur, pointing towards scopes to be improved in the model architecture and dataset diversity. Figure 3 depicts the plot of loss against epochs, the training and validation loss over five epochs. As shown in the first epoch, loss value for training and validation is high and continuously declined as the process of training moved on. This trend denotes the learning curve of the model and implies convergence towards low loss values; however, it still fluctuates within the validation loss, which may denote overfitting tendencies, implying that the need for more regularization techniques, larger datasets, or further dropout layers is required. Referring Figures 2 depict the accuracy trends graph and steady improvement of training accuracy across epochs. The validation accuracy reflects this trend and is not always smooth, as there may be some overfitting or just a lack of diversity in the dataset. Diversity and volume would most likely be improved with generalization to

unseen data. Confusion matrices shown in Figure 4 detail the strengths and weaknesses of this classification. The correct categories are very sparsely spread along the diagonal with excellent precision for some shot types, like drive and pull. Misclassifications occur mostly between very similar visual categories, like cut and flick or slog and sweep. This calls for better feature extraction techniques that can identify slight differences in a player's movements and angles of shots.
It thus points out the necessity of dealing with dataset limitations, especially in terms of size and class balance. Advanced data augmentation techniques, including synthetic sample generation or targeted resampling, would overcome these challenges. The model may benefit from learning motion patterns through the development of a 3D convolutional neural network or by refining the LSTM architecture.
In conclusion, there are glaring opportunities for improvement as highlighted by the visual output and comprehensive analytics. If more data were used, and the architecture optimized, this proposed system would perform incredibly well and be of use to cricket analytics.

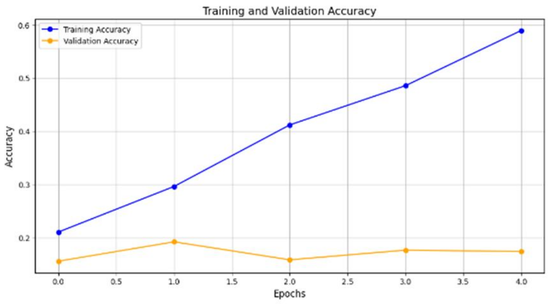

Figure 2 learning curve for accuracy trends

Figure 3 learning curve for loss trends

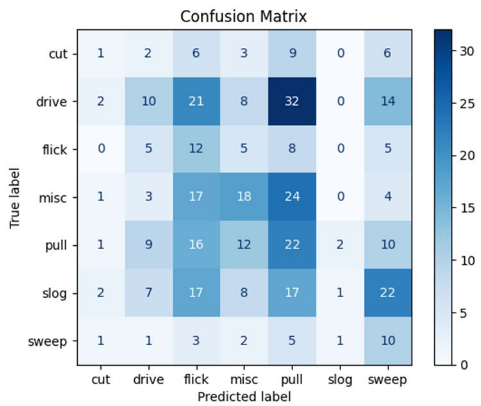

Figure 4. Confusion Matrix

V. Conclusion

The system provides a CNN-LSTM framework for cricket shot detection, primarily focused on extracting spatial and temporal features. Despite achieving moderate accuracy, the proposed system shows how computer vision may be applied to sports analytics. The results here underscore the relevance of robust datasets, advanced augmentation methods, and hybrid architectures toward enhancing model performance. Future work direction may focus on the increasing the size of the dataset with varied match conditions and shot variations. Also, should consider the augmentation techniques to improve the handling of complex data patterns. Alternative CNN architectures should be tested along with hyperparameter tuning for better accuracy and generalization. The system deployment in real-time scenarios, such as live match analysis to provide immediate feedback to the players and coaches.

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