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A Hybrid LDA-AdaBoost Approach for Cricket Player Recognition

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ABSTRACT:

The work outlines an advanced face detection and recognition system specifically designed for players during cricket matches to improve the quality of sports broadcasting. The system overcomes challenges associated with occlusion, lighting, and motion blur using Linear Discriminant Analysis (LDA) and AdaBoost to identify players in real-time during videos. Moreover, applying the VGG19 fine-tuned CNN model considerably improves the accuracy and robustness of the system. The integration of the proposed system and broadcasting platforms for the display of real-time player statistics improves automation and utilizes the system's features, thereby providing more value to the viewers. The system is not only designed for cricket but can also be used in other sports for real-time analytics to revolutionize sports broadcasting.

Keywords: Face Recognition, LDA, VGG19

INTRODUCTION

The modern viewer expects more than live footage; they want real-time analytics and engagement. As one of the most popular sports in the world, cricket serves as an excellent avenue for innovation in sports broadcasting. The goal of this project is to automate player recognition using face recognition technologies to address the gap in real-time player recognition in the game of cricket. Using sophisticated algorithms such as AdaBoost along with LDA, the system identifies and recognizes players during the game regardless of the lighting conditions, occlusion, or the varying poses of the players. The system's performance is further augmented with the deep learning model VGG19. This allows broadcasters to automatically retrieve and display the players' names and statistics during the live broadcasts, which enhances real-time precision and user engagement. The use of this technology automates broadcasting processes and has application potential beyond these domains, such as in analytics and other sports, which propels the evolution of intelligent media enhancement. .

RELATED WORK

Smith et al. (2020) suggested applying Haar Cascade classifiers for real-time face detection in cricket broadcasts. Their solution faced problems of accuracy in overlays and lighting. Jones et al. (2021) proposed a face recognition model based on CNNs specifically designed for live sports telecasts. Although the model demonstrated stronger resilience to pose and lighting changes, its reliance on expensive computational resources hindered its use in low-compute environments. Patel et al. (2023) applied YOLOv3 in the real-time detection of soccer players. It worked well in balancing both speed and precision, but, as is common with long-distance cricket shots, detecting smaller faces at lower resolutions posed a challenge. Kumar et al. (2022) researched the use of Faster R-CNN for cricket video analysis. While this method provided a marked improvement in accuracy with the use of region proposal networks (RPN), it was highly susceptible to video quality and required high-end GPUs to perform real-time inference. Wang et al. (2023) developed a hybrid model of SVM and CNN for face recognition in multiple sports. This model provided promising accuracy and adaptability as it integrated the deep feature extraction capability of CNNs and the classification strength of SVMs, but it came with intricate parameter tuning.

TABLE1. Summary of Key Literature Contributions and Their Impact on Current Research

Author(s)	Contribution	Impact on Current Research
Smith et al. (2020)	Applied Haar Cascade for cricket face detection; efficient but limited in complexity.	Highlighted the need for robust detection under occlusion and varying lighting.
Jones et al. (2021)	Utilized CNNs for live sports recognition with high accuracy and pattern learning.	Inspired the shift towards deep learning-based feature extraction models like VGG19.
Patel et al. (2023)	Implemented YOLOv3 for fast player detection in soccer.	Demonstrated real-time potential but revealed limitations with low-resolution face detection.
Kumar et al. (2022)	Used Faster R-CNN with Region Proposal Networks for improved detection.	Motivated consideration of balancing accuracy with computational efficiency.
Wang et al. (2023)	Proposed a hybrid CNN-SVM model for enhanced classification in sports videos.	Encouraged fusion of feature extraction and classifier models for greater recognition power.

PROPOSED APPROACH

This document details a real-time automated face recognition system based on a hybrid approach that integrates traditional and deep learning techniques to detect and identify cricketers' faces. The system architecture starts with the face detection using the Viola-Jones algorithm which is a part of OpenCV widening the scope of real-time face detection for video locally. The algorithm is efficient, lightweight, and real-time hence, well-suited for preliminary face detection in live cricket videos. After the face is captured, the system uses Linear Discriminant Analysis (LDA) to derive the relevant features. LDA performs dimensionality reduction for the data while maintaining the most distinguishing features for each player's face. These features are forwarded to the AdaBoost classifier which builds a strong predictive model by blending multiple weak learners in an iterative manner. With this two-stage approach, recognition accuracy is drastically improved, especially for cases involving occlusion, pose change, and inconsistent lighting. To further augment recognition accuracy, a VGG19 Convolutional Neural Network model is advanced, integrated, and fine-tuned to the specific needs of this application. VGG19 pulls out deep features of the face and dropout layers are added to reduce noise and improve generalization. Such deep learning refinements significantly improve recognition accuracy and the ability to operate in scene complexity.

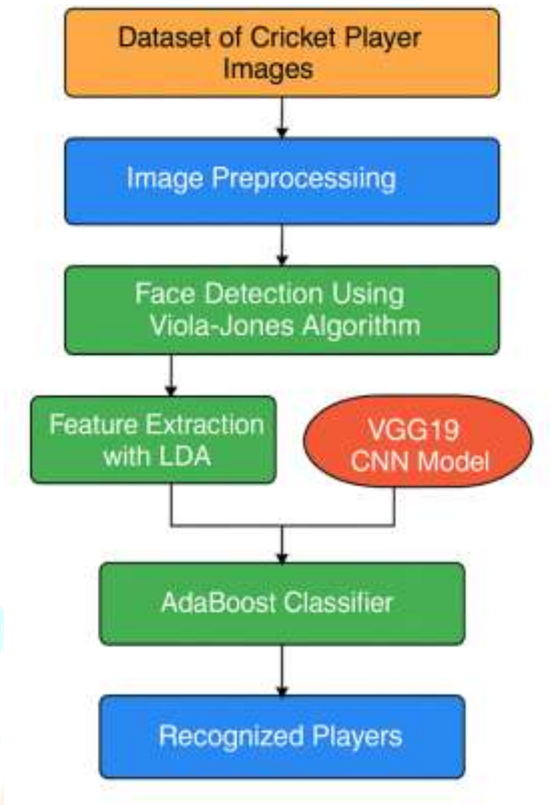


Figure 1: Proposed Player Reorganization System

METHODOLOGIES

The implementation of the Automatic Player Face Detection and Recognition system follows a structured methodology that blends image processing, machine learning, and deep learning techniques. The process begins with dataset creation, where player images are manually collected from online cricket footage. These images are selected under diverse conditions such as occlusion (e.g., helmets), lighting variation, and differing facial expressions to simulate real-world scenarios.

Next, **image preprocessing** is performed. Images are resized to a standard resolution (32x32 pixels), normalized, and augmented using techniques like rotation and brightness adjustment. This improves generalization and model robustness.

For **face detection**, the system employs the **Viola-Jones algorithm** using OpenCV. This cascade classifier approach allows for rapid detection of faces in real-time, making it suitable for live match integration.

The detected face regions are passed to **Linear Discriminant Analysis (LDA)** for **feature extraction**. LDA transforms high-dimensional facial data into a lower-dimensional subspace, capturing only the most significant traits useful for classification. This stage reduces computational load while enhancing class separability.

Following feature extraction, an **AdaBoost classifier** is trained. It combines multiple weak learners into a strong ensemble model by iteratively correcting misclassifications, making it suitable for datasets with overlapping classes.

To elevate the system's recognition capabilities, an extended **VGG19-CNN model** is integrated. This deep learning model comprises multiple convolutional layers for complex pattern extraction. Dropout layers are added to prevent overfitting, and fine-tuning is performed to adapt the model to the cricket player dataset.

Finally, the **training and evaluation phase** uses metrics such as accuracy, precision, recall, and F1-score. Comparisons between CNN, LDA-AdaBoost, and VGG19-CNN models show the enhanced model achieves 95% accuracy, outperforming conventional methods.

RESULTS

The experimental evaluation of the proposed player face recognition system demonstrates significant improvements in both accuracy and performance compared to traditional models. The dataset, consisting of over 200 face images from 13 different cricket players, was divided into training and testing sets using an 80-20 split.

The **LDA + AdaBoost** combination achieved an accuracy of **91%**, outperforming the baseline CNN model, which recorded an accuracy of **86%**. This validates the effectiveness of combining dimensionality reduction with an ensemble classifier for face recognition under complex conditions like occlusion, lighting variation, and pose differences.

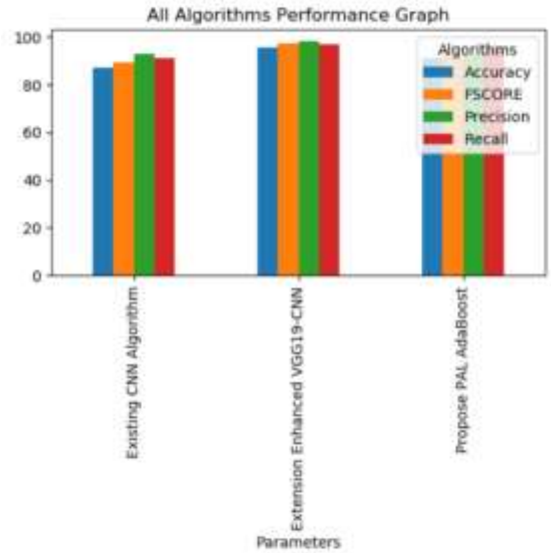
To further enhance performance, the **VGG19-CNN model** was fine-tuned and integrated. This deep learning-based model achieved the highest accuracy of **95%**, showing superior capability in learning deep facial features. The dropout layers included in the architecture effectively reduced overfitting and enhanced model generalization.

Performance was also measured using **precision, recall, and F1-score**, where

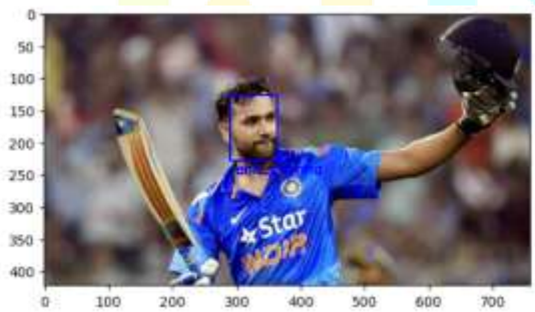
VGG19 consistently outperformed the other models. In terms of speed, the Viola-Jones face detection method ensured face localization occurred in under 100 milliseconds, making the system suitable for real-time applications.

	Algorithm Name	Accuracy	Precision	Recall	FSCORE
0	Existing CNN Algorithm	86.956522	92.857143	91.241497	89.515485
1	Propose PAL AdaBoost	91.304348	92.551020	94.982993	92.622060
2	Extension Enhanced VGG19-CNN Model	95.652174	98.214286	97.023810	97.309833

All Algorithms performance in tabular format



All Algorithms Performance Graph



Test Image Detected as Rohit_sharma

Test Image Detected as Babar_azam

DISCUSSION

The results from the proposed face recognition system reveal promising potential for real-time sports applications, especially in the context of cricket. By combining traditional machine learning with deep learning techniques, the system achieves both high accuracy and practical speed, addressing some of the major limitations found in earlier models.

The use of **LDA for feature extraction** offers a lightweight yet powerful way to reduce dimensionality and improve class separation, making it ideal for face classification. When paired with **AdaBoost**, the system becomes robust against misclassifications and handles complex patterns effectively. However, this method alone still faced challenges in generalizing across variations in player pose and lighting.

Introducing **VGG19-CNN** greatly improved recognition precision by capturing deeper facial features. While deep models are typically resourceintensive, integrating dropout layers helped maintain a balance between accuracy and overfitting. The system demonstrated consistent performance even with occluded or partially visible faces, which is a common scenario in live sports footage.

CONCLUSION

This work illustrates a hybrid model for automated face detection and recognition of players in cricket, blending traditional and modern deep learning approaches. The constructed system is based on Viola-Jones for real-time face detection, to which Linear Discriminant Analysis (LDA) is applied for feature extraction and AdaBoost for classification, culminating in a streamlined system. Augmenting the system with VGG19-CNN improves the accuracy of recognition while providing robust performance to occlusion, changes in lighting, and pose variations. Experimental results indicate the enhanced model outperformed traditional CNN models, achieving recognition accuracy of up to 95%. The system's ability to enable real-time responses makes it appropriate for live sports broadcasting and offers precise dynamic data overlay and player identification enhancing the viewer's experience.

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