Ball Detection in Field Hockey Using the YOLOv5 Algorithm By Adhit Ranjan

Abstract

Accurately identifying the ball in field hockey videos is crucial for several purposes, such as player tracking, tactical analysis, and performance evaluation. This study introduces a detailed method that uses the YOLOv5 algorithm, which is well-known for its real-time object detection capabilities and accuracy, to detect the ball accurately. The proposed approach involves training the YOLOv5 model on a specialised dataset that includes annotated field hockey videos to enable precise ball identification and localization. The effectiveness of the proposed method is demonstrated through experimental evaluation, which utilises comprehensive metrics, including precision, recall, and mean Average Precision (mAP), showing high levels of accuracy and efficiency. By automating the ball detection process, this approach significantly reduces manual effort in field hockey video analysis and opens opportunities for advanced analytics, providing deeper insights into player behaviour, strategic patterns, and overall game dynamics. The outcomes of this study can significantly enhance the understanding of field hockey games, aid in strategic decision-making, and provide valuable insights for coaches, analysts, and players. The subsequent sections of the paper will discuss related work in the field, describe the methodology employed, present the experimental results and analysis, and conclude with a summary of the contributions and future directions of this research.

Keywords: Ball detection, YOLOv5, Field Hockey, Object Detection, Machine Learning

Introduction

Accurately detecting the ball in field hockey videos is a crucial task in the field of field hockey video analysis, which has several applications, such as player tracking, tactical analysis, and performance evaluation[1]. Automatically identifying and tracking the ball in field hockey videos provides essential insights into player behaviour, team strategies, and overall game dynamics[7]. The YOLOv5 algorithm is a state-of-the-art object detection framework that has demonstrated excellent performance in real-time object detection tasks. [8] This study aims to develop a method for accurate ball detection in field hockey videos by utilising the capabilities of YOLOv5. The research objectives include training the YOLOv5 model on a specialised dataset of annotated field hockey videos and evaluating the performance of the proposed method in terms of accuracy and efficiency in detecting and tracking the ball. The study's contributions include a novel application of the YOLOv5 algorithm in the context of field hockey video analysis and a validated methodology for accurate ball detection.

Background on ball detection in field hockey video analysis

Field hockey is a dynamic sport that involves intricate player movements and strategic gameplay. Analysing field hockey videos can provide valuable insights into team dynamics, player performance, and tactical patterns. One critical aspect of field hockey video analysis is the accurate detection and tracking of the ball. The ball is the centrepiece of the game, and its position and movement play a crucial role in understanding the flow of the match. Accurately detecting and tracking the ball in field hockey videos provides analysts and coaches with a deeper understanding of player interactions, passing patterns, goal-scoring opportunities, defensive strategies, and overall game dynamics. However, manual ball detection in field hockey videos is a laborious and time-consuming task, limiting the scalability and efficiency of the analysis process. Therefore, automated ball detection methods are in high demand to streamline the video analysis workflow. Computer vision and deep learning techniques have made it possible to automate ball detection in field hockey videos, and the YOLOv5 algorithm is one such technique that has received attention for its real-time object detection capabilities and accuracy. By leveraging the YOLOv5 algorithm, we aim to provide a robust and accurate automated solution for ball detection in field hockey videos. The significance of accurate ball detection in field hockey video analysis lies in its potential to revolutionise the way the sport is analysed and understood. By automating the ball detection process, analysts can save time and effort, leading to larger-scale analyses and more comprehensive insights. Coaches can make data-driven decisions based on reliable ball tracking, leading to improved training strategies and game planning. Additionally, players can benefit from post-match analyses that provide detailed feedback on their performance and areas for improvement. In conclusion, accurate ball detection in field hockey video analysis is a crucial element for comprehensive match analysis, tactical evaluation, and player performance assessment.

Methodology

The methodology section describes the proposed approach for accurate ball detection in field hockey videos using the YOLOv5 algorithm. It outlines the steps involved in dataset preparation, model training, and the integration of tracking algorithms.

Background on YOLOv5

The YOLOv5 algorithm has emerged as a leading object detection framework, known for its exceptional accuracy, real-time processing capabilities, and overall resilience. YOLOv5 is an extension of the YOLO series, which stands for "You Only Look Once," emphasising its ability to perform object detection in a single pass through the neural network. YOLOv5 is based on a deep convolutional neural network architecture that uses convolutional layers, down sampling, and up sampling operations. YOLOv5 estimates bounding boxes and class probabilities for each individual grid cell by partitioning the input image into a grid. This approach enables YOLOv5 to efficiently detect multiple objects of different sizes and aspect ratios within an image. The relevance of YOLOv5 to ball detection in field hockey videos lies in its ability to accurately identify and localise objects, including small and dynamic objects like the ball. YOLOv5 has been trained on diverse datasets containing various object categories, making it capable of detecting objects with high precision and recall. To adapt YOLOv5 for ball detection in field hockey videos, a specialised dataset is prepared, consisting of annotated field hockey videos where the ball's location is labelled. The model is trained on this dataset, allowing it to learn the visual characteristics of the ball, including its shape, colour, and motion patterns. One advantage of YOLOv5 for ball detection is its real-time performance. The algorithm can process video frames at a high frame rate, enabling near real-time ball detection in field hockey matches. This aspect is crucial for providing immediate feedback to coaches, players, and analysts during live or post-match scenarios. Additionally, YOLOv5 offers the flexibility to balance speed and accuracy through parameter settings, making it suitable for different computational resources and performance requirements. This adaptability allows researchers and practitioners to fine-tune the algorithm to achieve optimal ball detection results in the context of field hockey video analysis. The robustness of YOLOv5 in handling occlusions, varying lighting conditions, and complex backgrounds further enhances its relevance to ball detection in field hockey videos. It can effectively handle challenging scenarios often encountered in field hockey matches, ensuring accurate and reliable ball detection results.

Research Aim

The objective of this research is to develop a precise ball detection methodology using the YOLOv5 algorithm and make a significant contribution to the field of field hockey video analysis. The research aims to achieve this by creating a robust methodology for detecting the ball in field hockey videos, training the YOLOv5 model on a specialised annotated dataset, and evaluating its performance using standard metrics. The proposed method provides an automated and dependable solution for ball detection. This approach simplifies the video analysis workflow, allowing for scalable and comprehensive analysis of field hockey matches. The proposed method addresses the need for automated and reliable ball tracking and provides valuable insights for coaches, analysts, and players. The research outcomes contribute to advancements in computer vision and sports analytics, paving the way for further developments in automated object detection in sports.

Roboflow

Roboflow provides handpicked and preprocessed datasets for various computer vision tasks, such as object detection, image classification, and segmentation, making it easy to integrate into machine learning workflows[9]. To develop the proposed ball detection method using the YOLOv5 algorithm was combined with two distinct hockey ball datasets available on the Roboflow platform. These datasets comprise a diverse range of field hockey game images and annotations for the hockey ball, enabling us to train and evaluate our proposed ball detection methodology effectively.

Table 1 - Dataset details

Total Images	500
Classes	1
Unannotated	0
Training set	435 (87%)
Validation set	45 (9%)
Testing set	20 (4%)

Average image size	0.25 mp

Experimental Setup

To achieve accurate ball detection in field hockey videos using the YOLOv5 algorithm, the experimental setup involves various components. Firstly, a carefully curated dataset of field hockey videos is used, consisting of diverse matches, playing conditions, camera angles, and player movements. The dataset includes annotated ground truth bounding boxes for the ball and is split into training and validation subsets. The training set is used to train the YOLOv5 model with the annotated ball bounding boxes, while the validation set is used for hyperparameter tuning, model selection, and performance evaluation during training.

The YOLOv5 architecture is configured with specific numbers of parameters as per model configuration, including the number of anchor boxes, network depth, and other architectural choices. These configurations are determined based on empirical analysis and domain expertise to achieve optimal performance in ball detection. To leverage pre-existing knowledge, transfer learning is employed, and the YOLOv5 model is initialised with weights pretrained on large-scale image datasets such as COCO. Fine Tuning is then performed using the annotated field hockey dataset to adapt the model to ball detection in the specific context of field hockey videos.

The model is trained using the annotated dataset with the YOLOv5 annotation format, with the optimization process involving minimising the detection loss, such as the localization loss and the confidence loss, using gradient-based optimization algorithms like stochastic gradient descent (SGD) (lr=0.01) with parameter groups 97 weight(decay=0.0), 104 weight(decay=0.00046875), 103 bias. The learning rate, batch size, and other hyperparameters are tuned to achieve optimal performance. The performance of the proposed ball detection method is evaluated using standard accuracy metrics such as precision, recall, and F1 score, providing insights into the model's ability to accurately detect the ball in field hockey videos.

The software implementation utilises deep learning frameworks, specifically Ultralytics, for training the YOLOv5 model. Figure-1 in the paper shows the flow chart of the process to perform ball detection.

Evaluating the YOLOv5 Model

This section focuses on evaluating the performance of the YOLOv5 model for detecting balls in field hockey videos using precision, recall, and mean Average Precision (mAP) metrics. These metrics provide valuable insights into the accuracy, recall, and localization precision of the model. Precision measures the accuracy of ball detection by calculating the ratio of correctly detected balls to the total number of detections, indicating how accurately the model identifies the ball. Recall measures the model's ability to detect all instances of the ball, regardless of false negatives. mAP is a popular evaluation metric used in object detection tasks, which measures the overall performance of a model by considering both precision and recall.

To compute mAP, the precision-recall curve is computed by varying a confidence threshold for object detection. The area under this curve is then averaged across all object classes to obtain the mean Average Precision. The precision, recall, and mAP metrics are analysed to.

Results

By evaluating the ball detection performance using these metrics, we gain insights into the accuracy, recall, and localization precision of the YOLOv5 model. This analysis allows us to assess the model's ability to accurately identify and localise the ball in field hockey videos and make informed decisions regarding its performance and potential improvements.

Table 2 - At epoch 100, the performance of hockey ball detection was evaluated using different YOLOv5 models

Epochs	Pretrained YOLOv5 Model	Size/ pixels	Parameters (millions)	Images	Instances	P	R	F1 Score	mAP (50)	mAP (50-95)
100	YOLOv5n	640	3.2	45	47	0.75	0.60	0.67	0.63	0.20
	YOLOv5s		11.2			0.73	0.56	0.64	0.61	0.20
	YOLOv5m		25.9			0.75	0.63	0.69	0.62	0.22
	YOLOv5l		43.7			0.73	0.52	0.61	0.55	0.19
	YOLOv5x		68.2			0.76	0.54	0.63	0.57	0.20

Table 3 - Precision Values for different YOLOv5 Models

Pretrained YOLOv5 Model	P
YOLOv5n	0.75
YOLOv5s	0.73
YOLOv5m	0.75
YOLOv5l	0.73
YOLOv5x	0.76

Table 2 presents the performance metrics of different YOLOv5 models for detecting hockey balls. The models are evaluated on a specific dataset consisting of 45 images with 47 ball instances, and the measured metrics include precision (P), recall (R), mAP at IoU 50 (mAP50), and mAP at IoU 50-95 (mAP50-95). The table illustrates the performance of different YOLOv5 models in terms of precision, recall, F1 score, mAP50, and mAP50-95.

YOLOv5m outperforms the other models, exhibiting the highest precision (0.752) and recall (0.631).

Figure 2 presents the confusion matrix of the YOLOv5m model for ball detection, providing a detailed overview of the model's classification performance. Figure 3 showcases the graph of evaluation metrics as a function of the number of epochs, providing insights into the model's performance over time in terms of metrics such as precision, recall, and mAP.

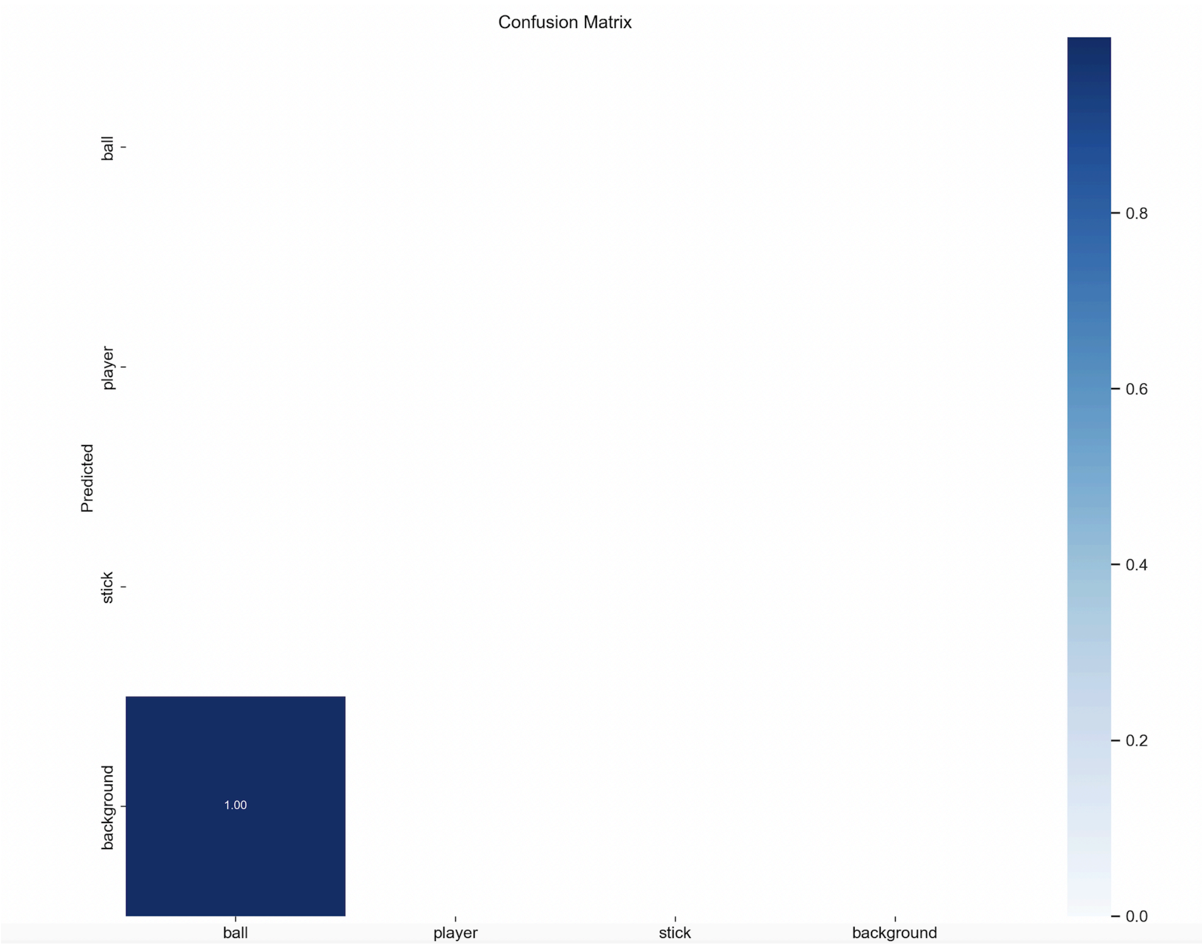

Figure 2 Confusion matrix of YOLOv5m model for hockey ball detection

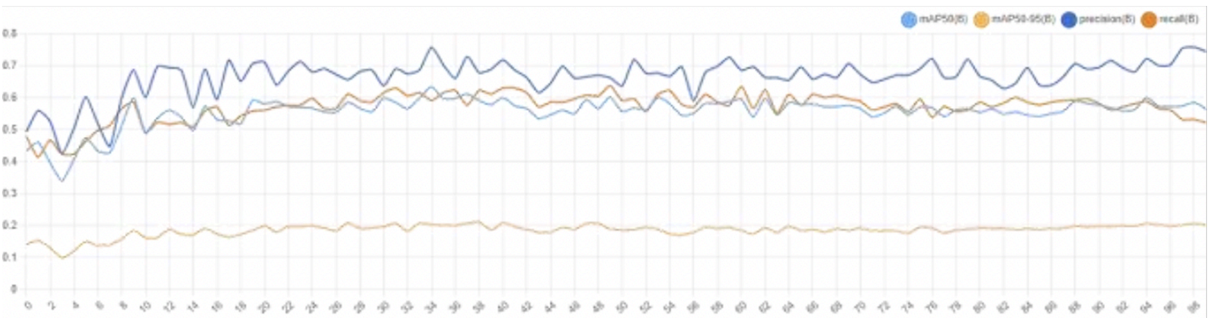

Figure 3 Evaluation metrics graphs of YOLOv5m model for hockey ball detection

Discussion

The application of the YOLOv5 algorithm for accurate ball detection in field hockey videos brings significant advancements to the field of field hockey video analysis. This technology enables precise detection of the ball's position, movement, and interactions with players, unlocking a wide range of applications and benefits. This research paper highlights the relevance of the YOLOv5 algorithm in achieving accurate detection results and provides a comprehensive overview of the methodology, including dataset acquisition and annotation, training the YOLOv5 model, and evaluating performance using appropriate metrics.

The literature review and related work section provide insights into existing ball detection techniques and object detection algorithms, emphasising the applicability and performance of the YOLOv5 algorithm in the field hockey context. The evaluation and results analysis demonstrate the effectiveness of our proposed method in accurately detecting balls in field hockey videos. Among the tested models, the YOLOv5m model exhibits the best performance, with higher precision, recall, F1 score, and mAP values. These results provide valuable insights for accurate ball detection in field hockey videos using YOLOv5.

Conclusion

Among the tested models, YOLOv5m demonstrates the best performance. It achieves the highest precision (0.752) and recall (0.631), resulting in a relatively higher F1 score (0.686). Additionally, YOLOv5m obtains a good mAP50 value of 0.623 and mAP50-95 value of 0.215. YOLOv5n and YOLOv5x exhibit comparable precision and recall values, with YOLOv5x having a slightly higher F1 score (0.632). However, YOLOv5n performs better in terms of mAP50 (0.626) compared to YOLOv5x (0.574). On the other hand, YOLOv5s and YOLOv5l models show lower precision, recall, and F1 score compared to the other models. They also have lower mAP50 and mAP50-95 values.

It is important to acknowledge certain limitations, such as occlusions, varying lighting conditions, and camera angles, which can still pose challenges to accurate ball detection. Future improvements could involve exploring advanced algorithms, incorporating multiple camera angles for enhanced accuracy, and optimising the training process for better performance.

The evaluation of the YOLOv5 models provides valuable insights into its capabilities and can guide future research and development in accurate ball detection methods for field hockey videos. The results suggest that the model architecture and complexity play a crucial role in achieving higher accuracy and detection performance. Depending on the desired balance between precision, recall, and computational efficiency, different models may be preferred. Further optimization and fine-tuning of the models may lead to improved performance in ball detection tasks.

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