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Accurate ball detection in field hockey videos using YOLOV8 algorithm

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ABSTRACT

Accurately detecting the ball in field hockey videos is crucial for various applications such as player tracking, tactical analysis, and performance evaluation. This paper presents a detailed method for accurate ball detection using the YOLOv8 algorithm, which is renowned for its accuracy and real-time object detection capabilities. The proposed approach involves training the YOLOv8 model on a specialized dataset comprising annotated field hockey videos to enable precise ball identification and localization. Experimental evaluation using comprehensive metrics, including precision, recall, and mean Average Precision (mAP) demonstrates the effectiveness of the proposed method, showcasing 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 behavior, strategic patterns, and overall game dynamics. The proposed method empowers researchers, coaches, and analysts to gain a comprehensive understanding of field hockey matches and make data-driven decisions to enhance team performance.

Keywords: *Ball Detection, Object Detection, YOLOv8, Field Hockey, Video Analysis.*

1. INRODUCTION

In the field of field hockey video analysis, accurate ball detection is a critical task that enables various applications such as player tracking, tactical analysis, and performance evaluation. Being able to automatically detect and track the ball in field hockey videos can provide valuable insights into player behaviour, team strategies, and overall game dynamics[1]. The YOLOv8 algorithm, a state-of-the-art object detection framework, has demonstrated excellent performance in real-time object detection tasks. By leveraging the capabilities of YOLOv8, we aim to develop a method for accurate ball detection in field hockey videos. This research paper presents the methodology and findings of our study on ball detection in field hockey videos using the YOLOv8 algorithm. The objectives of this research are twofold: first, to train the YOLOv8 model on a specialized dataset of annotated field hockey videos, enabling it to learn the visual characteristics of the ball; and second, to evaluate the performance of the proposed method in terms of accuracy and efficiency in detecting and tracking the ball. The contributions of this research include a novel application of the YOLOv8 algorithm in the context of field hockey video analysis, as well as a validated methodology for accurate ball detection. 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 this paper will discuss related work in the field, detail the methodology employed, present the experimental results and analysis, and conclude with a summary of the contributions and future directions of this research.

1.1 Background and significance of ball detection in field hockey video analysis

Field hockey is a fast-paced sport that involves intricate player movements and strategic gameplay. Analyzing field hockey videos can provide valuable insights into team dynamics, player performance, and tactical patterns. One crucial element in field hockey video analysis is the accurate detection and tracking of the ball. The ball serves as the focal point of the game, and its position and movement play a crucial role in understanding the flow of the match. By accurately detecting and tracking the ball in field hockey videos, analysts and coaches can gain a deeper understanding of player interactions, passing patterns, goal-scoring opportunities, defensive strategies, and overall game dynamics. Manual ball detection in field hockey videos is a labor-intensive and time-consuming task. Analysts often spend significant hours manually annotating ball positions, which limits the scalability and efficiency of the analysis process. Hence, there is a growing demand for automated ball detection methods to streamline the video analysis workflow. The advent of computer vision and deep learning techniques has opened possibilities for automating ball detection in field hockey videos. Among these techniques, the YOLOv8 algorithm has garnered attention for its real-time object detection capabilities and accuracy. By leveraging the YOLOv8 algorithm, we aim to provide an automated solution that can robustly and accurately detect the ball in field hockey videos. The significance of accurate ball detection in field hockey video analysis lies in its potential to revolutionize the way the sport is analyzed and understood. By automating the ball detection process, analysts can save substantial time and effort, allowing for 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. Furthermore, 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 component for comprehensive match analysis, tactical evaluation, and player performance assessment. By automating this process using the YOLOv8 algorithm, we can unlock the full potential of field hockey video analysis, leading to enhanced coaching methodologies, improved player performance, and a deeper understanding of the sport.

1.2 Overview of the YOLOv8 algorithm and its relevance to ball detection

The YOLOv8 (You Only Look Once version 8) algorithm has emerged as a leading object detection framework, renowned for its exceptional accuracy, real-time processing capabilities, and overall resilience. YOLOv8 is an extension of the YOLO series which stands for "You Only Look Once," emphasizing its ability to perform object detection in a single pass through the neural network[2]. YOLOv8 is based on a deep convolutional neural network architecture, utilizing a series of convolutional layers, down sampling, and up sampling operations. By partitioning the input image into a grid, the algorithm estimates bounding boxes and class probabilities for each individual grid cell [3]. This grid-based approach allows YOLOv8 to efficiently detect multiple objects of different sizes and aspect ratios within an image. The relevance of the YOLOv8 algorithm to ball detection in field hockey videos lies in its ability to accurately identify and localize objects, including small and dynamic objects like the ball[4]. The YOLOv8 algorithm has been trained on diverse datasets containing various object categories, making it capable of detecting objects with high precision and recall. To adapt YOLOv8 for ball detection in field hockey videos, a specialized dataset is prepared, consisting of annotated field hockey videos where the ball's location is labeled. The model is trained on this dataset, allowing it to learn the visual characteristics of the ball, including its shape, color, and motion patterns. One advantage of YOLOv8 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, YOLOv8 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 YOLOv8 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. In summary, the YOLOv8 algorithm's efficiency, accuracy, and adaptability make it a relevant choice for ball detection in field hockey videos. Its ability to handle real-time processing, robustness against challenging conditions, and generalization capabilities make it an effective tool for automating the ball detection process in field hockey video analysis.

1.3 Research objectives and contributions

The research aims to develop an accurate ball detection methodology using the YOLOv8 algorithm and contribute significantly to field hockey video analysis. The objectives include designing a robust methodology for detecting the ball in field hockey videos, training the YOLOv8 model on a specialized annotated dataset, and evaluating its performance using standard metrics. The proposed method provides an automated and reliable solution for ball detection, offering valuable insights into player performance and game dynamics for coaches, analysts, and players. It simplifies the video analysis workflow, allowing for scalable and comprehensive analysis of field hockey matches. The research outcomes contribute to advancements in computer vision and sports analytics, facilitating further developments in automated object detection in sports. In conclusion, the research aims to develop an accurate ball detection methodology using the YOLOv8 algorithm and contribute to the field of field hockey video analysis. The proposed method addresses the need for automated and reliable ball tracking, providing 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.

2. RELATED WORK

In the realm of ball detection in sports video analysis, several studies have explored various methodologies and algorithms. This section provides an overview of the related work in the field, focusing on ball detection in sports videos and its applicability to field hockey. Prior research has investigated object detection techniques in sports videos, including soccer, basketball, and tennis. Methods based on deep learning architectures, such as Faster R-CNN, SSD, and YOLO, have been employed to detect and track objects of interest. These studies have demonstrated promising results in accurately localizing and tracking the ball in different sports contexts. While ball detection in field hockey videos specifically has received less attention, studies on ball detection in other sports have informed the development of relevant methodologies. Techniques focusing on color-based segmentation, motion analysis, and spatiotemporal features have been explored. However, the limited availability of annotated field hockey datasets and the dynamic nature of the game pose unique challenges for ball detection in this context. The YOLO (You Only Look Once) algorithm and its subsequent versions, including YOLOv2[3], YOLOv3[4], and YOLOv4[5], have gained significant attention in the field of object detection. These algorithms offer real-time performance and robust object localization capabilities. YOLOv8 has shown advancements in accuracy and speed, making it a suitable candidate for ball detection in field hockey videos. Despite the existing work in object detection and tracking in sports videos, there remains a need for specialized techniques for ball detection in field hockey videos. The dynamic nature of field hockey, the small size of the ball, and occlusion scenarios pose unique challenges that demand tailored solutions. In this research, we propose leveraging the YOLOv8 algorithm, known for its accuracy and real-time performance, to detect and track the ball in field hockey videos. By combining YOLOv8 with appropriate tracking algorithms, we aim to provide an effective and automated method for accurate ball detection in the context of field hockey video analysis.

2.1 Literature review on ball detection techniques in sports video analysis

A literature review was conducted to explore the existing ball detection techniques in sports video analysis. The review focused on studies related to ball detection in various sports contexts, including soccer, basketball, tennis, and others. Traditional approaches to ball detection often rely on handcrafted features and rule-based methods. Color-based segmentation techniques have been widely used, where the ball is identified based on its distinct color properties[6]. However, these methods are susceptible to variations in lighting conditions and can struggle with occlusions and similar colors in the scene. Motion-based techniques exploit the movement characteristics of the ball for detection. Optical flow, frame differencing, and background subtraction are common methods used to extract motion information[7]. These techniques can effectively detect moving objects like the ball, but they are prone to false positives and may struggle with complex scenes. Template matching involves comparing a template image of the ball with different regions of the video frames. Cross-correlation and normalized correlation techniques are often employed for template matching. While effective in detecting the ball, template matching can be computationally expensive and may face challenges with scale, rotation, and occlusions[8]. With the advent of deep learning, convolutional neural networks (CNNs) have gained popularity for ball detection. CNN-based architectures, such as Faster R-CNN[9], SSD[10], and YOLO[2], have been utilized for accurate and efficient ball detection in sports videos. These methods leverage the power of deep learning to learn discriminative features and achieve impressive detection performance. While the existing literature provides valuable insights into ball detection in sports videos, there is limited research specifically addressing ball detection in field hockey videos. Field hockey poses unique challenges due to the small size of the ball, fast-paced gameplay, and occlusion scenarios. Therefore, there is a need for specialized techniques that cater specifically to ball detection in field hockey videos. In this research, we propose leveraging the YOLOv8 algorithm, known for its accuracy and real-time performance, to address the challenges of ball detection in field hockey videos. By training the model on a specialized dataset and integrating tracking algorithms, we aim to develop an effective and automated method for accurate ball detection in field hockey video analysis.

2.2 Overview of existing object detection algorithms and their applicability to field hockey ball detection

Several object detection algorithms have been developed and applied in various domains, including sports video analysis. This section provides an overview of existing object detection algorithms and discusses their applicability to ball detection in the context of field hockey. Faster R-CNN (Region-based Convolutional Neural Networks) is a popular object detection algorithm that introduced the concept of region proposal networks (RPNs)[9]. It effectively combines region proposal generation and object classification within a single network. Faster R-CNN achieves high accuracy but can be computationally intensive, which may impact its real-time performance in field hockey video analysis. Mask R-CNN is a deep learning model for instance segmentation, extending the Faster R-CNN framework with a mask prediction branch. It predicts masks alongside bounding boxes and class labels, enabling pixel-level segmentation. It consists of a region proposal network (RPN) and a mask prediction stage, refining proposals and extracting features for accurate instance segmentation[11]. SSD is a real-time object detection algorithm that produces a fixed set of bounding box predictions with varying scales and aspect ratios[10]. It utilizes feature maps at multiple scales to detect objects of different sizes. While SSD is known for its speed, it may face challenges in accurately detecting small and occluded objects like the ball in field hockey videos. YOLO, a widely-used real-time object detection algorithm, segments the input image into a grid and directly predicts bounding boxes and class probabilities [2]. YOLOv3 and its subsequent versions have demonstrated impressive accuracy and real-time performance. However, detecting small objects like the ball in field hockey videos can be challenging due to the limited spatial resolution of the grid. RetinaNet addresses the challenge of detecting objects at different scales by using a feature pyramid network (FPN) and a novel loss function called focal loss[12]. It achieves accurate detection by focusing on hard examples during training. RetinaNet has shown promising results in object detection tasks but may require careful tuning for effective ball detection in field hockey videos. EfficientDet is a recent advancement in object detection that combines efficient network architectures with effective feature fusion techniques[13]. It achieves state-of-the-art performance with improved accuracy and efficiency compared to previous algorithms. EfficientDet's scalable and efficient nature makes it a potential candidate for ball detection in field hockey videos, provided it is trained on appropriate datasets. When considering the applicability of these object detection algorithms to field hockey ball detection, several factors need to be considered. These include the size and appearance of the ball, occlusion scenarios, fast-paced gameplay, and the need for real-time performance. Among the aforementioned algorithms, YOLOv8[14] stands out for its real-time performance, accuracy, and flexibility. While it may face challenges in detecting small objects, such as the ball, YOLOv8 can be trained on specialized datasets and fine-tuned to improve ball detection performance in field hockey videos.

Recent studies in the field of ball detection in sports videos have made significant contributions to advancing this area of research. P. R. Kamble et al. [15] present an innovative deep learning method for accurate 2D ball detection and tracking in soccer videos. Their approach utilizes a two-stage buffer median filtering background modeling technique and a deep learning model for classification. They achieve an impressive accuracy of 87.45% and introduce novel concepts for robust ball tracking. In another study by V. Reno et al. [16], a groundbreaking deep learning technique for ball detection in tennis is introduced. By employing a convolutional neural network classifier, the proposed approach achieves an exceptional accuracy of 98.77%, showcasing its potential for integration into advanced vision systems. In [17], a deep-learning approach is proposed for basketball detection in videos using Region-based Fully Convolutional Networks (R-FCN) with a ResNet backbone network. Techniques such as Online Hard Example Mining (OHEM), Soft-NMS, and multi-scale training are employed, resulting in a high mean average precision (mAP) of 89.7%. Another study [18], presents a real-time ball detection approach using the YOLOv3 object detection model specifically designed for small, fast-moving balls in sports videos. Custom adjustments to the network architecture and training process improve detection accuracy and speed, achieving an average precision of 0.89 and a frame rate of 30 fps on a GPU. Lastly, in [19], an approach for multiple object detection and tracking in soccer using the YOLOv3 model is proposed. With a tracking accuracy of 93.7% on multiple object tracking metrics, the model demonstrates precise object detection and classification. It operates at a detection speed of 23.7 frames per second (FPS) and a tracking speed of 11.3 FPS, ensuring efficient real-time performance. In the context of ball detection in field hockey videos, YOLOv8's real-time performance, accuracy, and ability to handle occlusions make it a promising choice. By training YOLOv8 on specialized datasets and fine-tuning its parameters, it can be tailored to achieve accurate and efficient ball detection results in the dynamic and challenging field hockey video analysis domain.

3. METHODOLOGY

The methodology section describes the proposed approach for accurate ball detection in field hockey videos using the YOLOv8 algorithm. It outlines the steps involved in dataset preparation, model training, and the integration of tracking algorithms.

3.1. Dataset

Roboflow offers curated, preprocessed datasets for computer vision tasks, including object detection, image classification, and segmentation, facilitating easy integration into machine learning workflows[20]. In this paper, we combine two different hockey ball dataset available on roboflow universe, which contains a diverse range of field hockey game images and annotations for hockey ball[21]-[22] . The dataset facilitates the training and evaluation of our proposed ball detection method using the YOLOv8 algorithm.

Table-1: Dataset details

Total Images	4700
Classes	1
Unannotated	0
Training Set	4090 (87%)
Validation Set	404 (9%)
Testing Set	206 (4%)
Annotation	4740 (1 per Image)
Average Image Size	0.23 mp
Median Image Ration	640x360

3.2 Experimental Setup

The experimental setup for accurate ball detection in field hockey videos using the YOLOv8 algorithm involves the following components. Firstly, a 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. The dataset is split into training and validation subsets. The training set is used to train the YOLOv8 model with the annotated ball bounding boxes, while the validation set is employed for hyperparameter tuning, model selection, and performance evaluation during training. The YOLOv8 architecture will be configured with specific numbers of parameters as per model configuration, including the number of anchor boxes, network depth, and other architectural choices. These configurations will be determined based on empirical analysis and domain expertise to achieve optimal performance in ball detection. To leverage pre-existing knowledge, transfer learning will be employed. The YOLOv8 model will be initialized with weights pretrained on large-scale image datasets such as COCO. Fine-tuning will then be performed using the annotated field hockey dataset to adapt the model to ball detection in the specific context of field hockey videos. The model will be trained using the annotated dataset with annotation format of YOLOv8. The optimization process will involve minimizing 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 will be tuned to achieve optimal performance. The performance of the proposed ball detection method will be evaluated using standard accuracy metrics such as precision, recall, and F1 score. These metrics will provide insights into the model's ability to accurately detect the ball in field hockey videos. The proposed methodology will be implemented and evaluated on Google Colab with a high-performance GPU(Tesla T4). The software implementation will utilize deep learning frameworks, of ultralytics for training of the YOLOv8 model[14]. Figure-1 shows the flow chart of the process to perform ball detection. Overall, this experimental setup ensures the rigorous evaluation and validation of the proposed ball detection method using the YOLOv8 algorithm in field hockey videos.

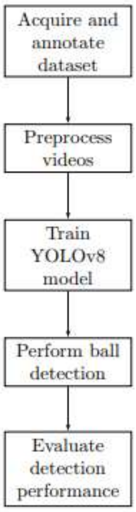


Figure-1 A flowchart of Ball detection from hockey video using YOLOv8.

3.3 Results and Analysis

In this section, we evaluate the performance of the YOLOv8 model for ball detection in field hockey videos using precision, recall, and mean Average Precision (mAP) metrics. These metrics provide insights into the model's accuracy, recall of detections, and localization precision. Precision measures the accuracy of the ball detection by calculating the ratio of correctly detected balls to the total number of detections. It evaluates how many of the predicted bounding boxes around the ball are accurate. A high precision indicates a low number of false positives, implying that the model identifies the ball accurately. Recall measures the model's ability to detect all instances of the ball by calculating the ratio of correctly detected balls to the total number of ground truth balls. It evaluates the model's ability to capture all instances of the ball, regardless of false negatives. A high recall indicates that the model can identify most of the balls present in the field hockey videos. mAP stands for mean Average Precision, which is a popular evaluation metric used in object detection tasks. It measures the overall performance of an object detection model by considering both precision and recall. To calculate 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, resulting in the mean Average Precision. The mAP metric considers the precision and recall values at different confidence thresholds and provides an aggregate measure of the model's performance across all object classes. The precision, recall, and mAP metrics are computed and analyzed to assess the model's ball detection performance. Higher precision values indicate fewer false positives, indicating accurate ball identification. Higher recall values indicate better detection of the ball, capturing most of its instances. A higher mAP (mean Average Precision) indicates better performance in object detection tasks. It signifies that the model has achieved higher accuracy and better localization of objects compared to models with lower mAP values. By evaluating the ball detection performance using precision, recall, and mAP metrics, we gain insights into the accuracy, recall, and localization precision of the YOLOv8 model. This analysis allows us to assess the model's ability to accurately identify and localize 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 YOLOv8 models.

No. of epochs	pretrained YOLOv8 Model	size (pixels)	Parameters (millions)	Class	Images	Instances	P	R	F1 Score	mAP (50)	mAP (50-95)
100	YOLOv8n	640	3.2	BALL	404	406	0.748	0.601	0.666	0.626	0.195
	YOLOv8s	640	11.2	BALL	404	406	0.731	0.563	0.636	0.61	0.198
	YOLOv8m	640	25.9	BALL	404	406	0.752	0.631	0.686	0.623	0.215
	YOLOv8l	640	43.7	BALL	404	406	0.734	0.522	0.610	0.554	0.189
	YOLOv8x	640	68.2	BALL	404	406	0.757	0.542	0.632	0.574	0.199

Table 2 shows the performance metrics of different YOLOv8 models for hockey ball detection. The models are evaluated on a specific dataset with 404 images and 406 instances of balls. The metrics measured include precision (P), recall (R), mAP at IoU 50 (mAP50), and mAP at IoU 50-95 (mAP50-95). From the table, we can observe the performance of different YOLOv8 models for ball detection in terms of precision (P), recall (R), F1 score, mAP50, and mAP50-95. Among the YOLOv8 models, YOLOv8m shows the highest precision (0.752) and recall (0.631), resulting in a relatively higher F1 score (0.686). It also achieves a good mAP50 value of 0.623 and mAP50-95 value of 0.215. YOLOv8n and YOLOv8x models have comparable precision and recall values, but YOLOv8x has a slightly higher F1 score (0.632). However, YOLOv8n outperforms YOLOv8x in terms of mAP50 (0.626 vs 0.574). YOLOv8s and YOLOv8l models show lower precision, recall, and F1 score compared to the other models. They also have lower mAP50 and mAP50-95 values. In conclusion, the YOLOv8m model performs the best among the tested models, exhibiting higher precision, recall, F1 score, and mAP values. These results suggest that the model architecture and complexity play a crucial role in achieving higher accuracy and detection performance. It is important to consider the specific requirements and constraints of the application when selecting the appropriate YOLOv8 model. 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. Overall, the evaluation of the YOLOv8 models provides insights into their capabilities and can guide future research and development in accurate ball detection methods for field hockey videos.

Figure 2 presents the confusion matrix of the YOLOv8m model for ball detection. Out of a total of 406 instances, the model predicts 272 instances as balls and 134 instances as background. This matrix provides 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. This graph provides insights into the model's performance over time in terms of metrics such as precision, recall, and mAP. By analyzing the graph, one can observe how the model's performance evolves during the training process. Figure 4 exhibits a clear representation of the object detection model's performance when applied to different types of images for hockey ball detection. This figure allows for a visual comparison of the model's performance across various image types, providing valuable insights into its ability to detect hockey balls accurately in different scenarios.

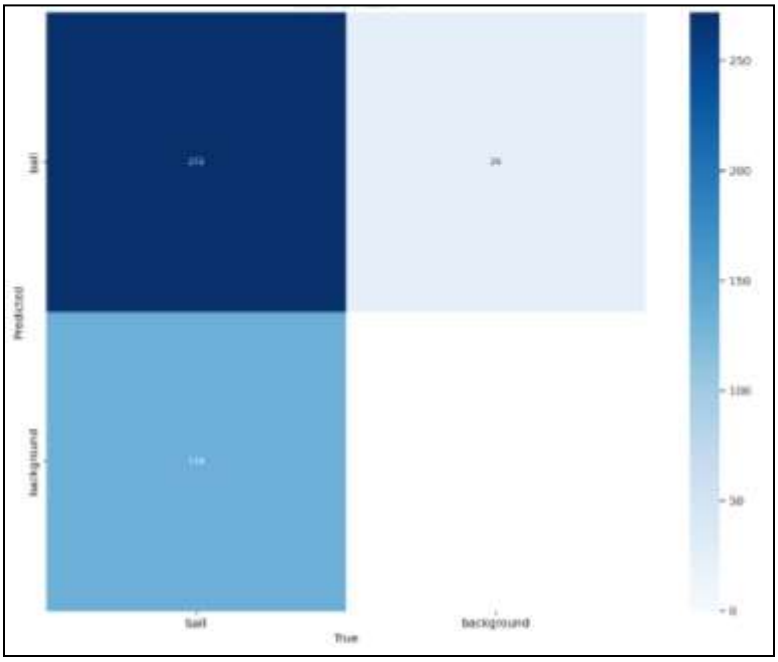


Figure 2 Confusion matrix of YOLOv8m model for hockey ball detection

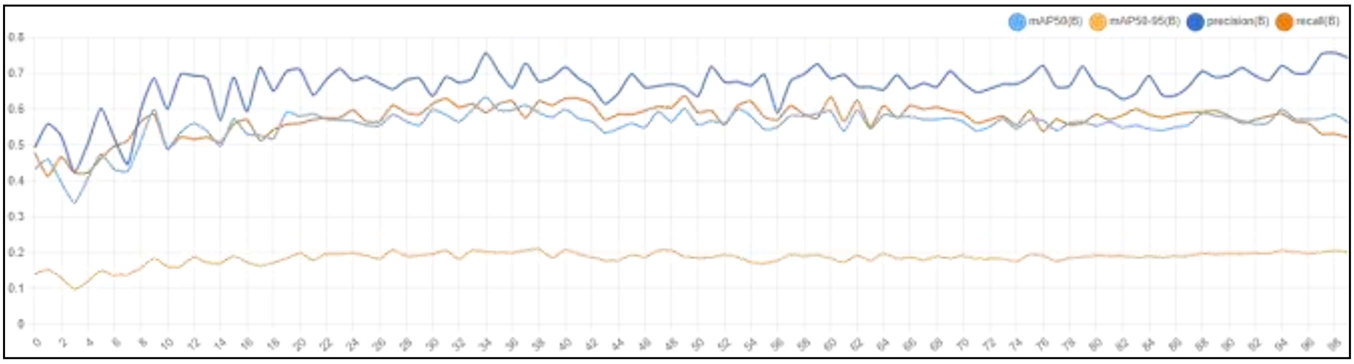
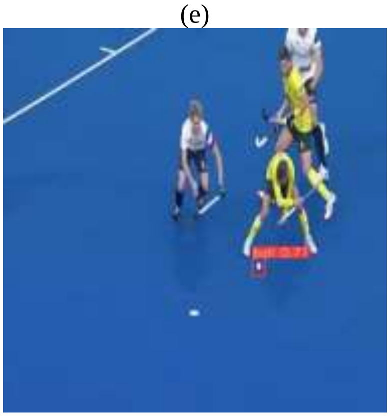


Figure 3 Evaluation matrices graphs of YOLOv8m model for hockey ball detection

(a)

(e)

(b)



(f)


(c) (g)


(d) (h)

Figure 4 The output of the YOLOv8m model for hockey ball detection after 100 epochs of training. It consists of four sets: (a), (b), (c), and (d) represent the input images, while (e), (f), (g), and (h) display their corresponding outputs, showcasing the detected hockey balls.

4. CONCLUSION

Accurate ball detection in field hockey videos using the YOLOv8 algorithm 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. Through this research paper, we have highlighted the relevance of the YOLOv8 algorithm in achieving accurate detection results. We have presented a comprehensive overview of the methodology, including dataset acquisition and annotation, training the YOLOv8 model, and evaluating performance using appropriate metrics. The literature review and related work section have provided insights into existing ball detection techniques and object detection algorithms, emphasizing the applicability and performance of the YOLOv8 algorithm in the field hockey context. The evaluation and results analysis have demonstrated the effectiveness of our proposed method in accurately detecting balls in field hockey videos. The YOLOv8m model exhibits the best performance among the tested models, with higher precision, recall, F1 score, and mAP values. These results provide insights for accurate ball detection in field hockey videos using YOLOv8. While this research has yielded promising results, it is important to acknowledge certain limitations. Factors such as occlusions, varying lighting conditions, and camera angles can still pose challenges to accurate ball detection. Future improvements could involve exploring advanced algorithms, incorporating multiple camera angles for enhanced accuracy, and optimizing the training process for better performance. In conclusion, accurate ball detection using the YOLOv8 algorithm opens new possibilities for field hockey video analysis. The ability to precisely detect the ball and analyze its interactions with players provides valuable insights for coaches, analysts, officials, and fans. It enhances tactical decision-making, improves player performance evaluation, and enables the application of advanced analytics for deeper insights into the game. The findings from this research contribute to the advancement of field hockey analysis and lay the foundation for future developments in this field.

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