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YOLOv8-Based Custom Object Detection System for Field Hockey Analysis

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ABSTRACT- The objective of this study is to create custom-trained models utilizing the YOLOv8 architecture to distinguish players in fast-paced field hockey environments. The research aims to enhance performance analysis and strategic decision-making in field hockey by introducing new insights and methodologies to optimize gameplay dynamics. The methodology involved training YOLOv8 models of varying sizes (Nano, Small, Medium, Large, Extra Large) on a self-annotated dataset using a GPU, with training conducted over multiple epochs at an image size of 640. Performance metrics such as precision, recall, F-1 score, and overall accuracy were evaluated for each model variant at 100 epochs. Results indicated that YOLOv8x models achieved high precision (0.832), recall (0.861), and an overall accuracy (mAP@0.5) of 85.70% after 100 epochs, with performance varying based on model size. Additionally, confusion matrices provided detailed insights into the classification performance of YOLOv8 models, highlighting areas for improvement and strengths in object detection. This study's innovation lies in the unique application of YOLOv8-based models for object detection in field hockey, contributing to a deeper understanding of their capabilities and limitations in sports analytics, particularly in player tracking, performance analysis, and strategic decision-making during field hockey matches.

Keywords: Sports Video Analysis, Custom Object Detection, YOLOv8, Deep Learning.

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1. INTRODUCTION

The rise of machine learning technology underscores the significance of object identification and tracking in sports videos. Moreover, the sports industry is actively exploring automated systems to enhance productivity across their organizations[1]. Field hockey stands as a dynamic and physically demanding sport, requiring a combination of speed, skill, and strategy from its players. As with any competitive sport, understanding the nuances of gameplay is crucial for teams and coaches seeking to optimize performance and gain a competitive edge[2]. Among the various aspects of analysis, player detection forms a fundamental component, providing insights into player positioning, movement patterns, and team interactions [3]. Traditionally, player detection in field hockey has relied on manual observation or basic computer vision techniques, which often struggle to keep pace with the rapid movements and complex interactions inherent in the sport [4]. Recognizing the limitations of these conventional methods, researchers have turned to advanced machine learning techniques, particularly deep learning-based object detection, to tackle the challenges of player detection in field hockey matches [5]. The You Only Look Once (YOLO) framework has emerged as a leading contender in the realm of object detection, offering real-time performance coupled with high accuracy [6]. With its ability to detect and localize objects in images or video frames in a single forward pass of a neural network, YOLO has garnered significant attention across various domains, including sports analytics [7].

In recent advancements, YOLOv8 has enhanced the capabilities of the YOLO architecture, showcasing improved accuracy, speed, and efficiency. This study aims to investigate the potential of YOLOv8 in field hockey player detection by

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harnessing its advancements. Through the training of customized models on annotated field hockey footage, our goal is to create a reliable system that can accurately detect players in real-time. This endeavor is poised to revolutionize performance analysis and strategic decision-making in the realm of field hockey. Illustrated in Figure 1 are distinct playing scenarios from a field hockey match, with labeled segments (a), (b), (c), and (d) likely representing various positions or situations within the game.

(a)

(b)

(c)

(d)

Figure 1. (a),(b),(c), and (d) Shows the different playing scenario in field hockey match.

1.1 Related Works

While the application of deep learning in sports analytics has gained momentum in recent years, research specifically targeting player detection in field hockey remains relatively limited. Existing studies in the domain of field hockey analytics have predominantly focused on manual analysis or basic computer vision techniques, often overlooking the potential of advanced machine learning approaches.

Liu, et al.(2009) propose a method for unsupervised detection, labeling, and tracking of multiple players in broadcast soccer videos using background subtraction, boosting with Haar features, unsupervised clustering, and MCMC data association [8]. Renò, et al.(2017) Renò et al. (2017) introduce a tennis coaching system that leverages hardware and software to track players and the ball, automatically annotating videos with 3D ball trajectories and scores to aid coaches in analyzing player performance during training and matches [9]. Han et al. (2018) provide a comprehensive review of recent advancements in object detection, delving into various detection types, exploring cutting-edge techniques like deep learning, analyzing benchmark datasets, comparing results, and offering insights into the connections between detection methods while also addressing unsolved challenges and future directions in the field [10]. Pobar and Ivasic-Kos (2020) developed a novel approach to tackle the challenges of detecting players and balls in handball images for action recognition, such as small ball size, appearance variations, occlusion, and player posture, by comparing YOLOv2-based models on a custom handball dataset, with the YPB model emerging as the top performer, achieving the highest average precision for both person detection and, notably, ball detection on distant objects and the custom dataset [11]. Patel and Kamdar (2023) introduce a YOLOv3 model for hockey video object detection, trained on a custom dataset. It automates player, team, and ball identification, aiding performance analysis in hockey broadcasts, showcasing the efficiency of deep learning in sports analytics[12]. Outside of field hockey, deep learning-based object detection has seen significant advancements in other sports such as soccer, basketball, and football. For instance, Naik and Hashmi (2021) proposes a YOLOv3-based system for ball and player detection in soccer videos, achieving high accuracy without data augmentation. It outperforms existing

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models in handling occlusion and paves the way for advanced player analytics like pass detection and heat maps[13]. Additionally, recent iterations of the YOLO framework, including YOLOv4 and YOLOv5, have further expanded the capabilities of object detection in sports analytics, setting the stage for innovative applications in field hockey and beyond.

Despite progress in technology, there is still a lack of research on detecting players in field hockey. This study aims to fill this gap by using a special system called YOLOv8 to detect players in field hockey games better. This could help improve how we analyze player performance and make strategic decisions in field hockey.

2. METHODOLOGY

2.1 Dataset Acquisition and Annotation

In the world of computer vision, making precise and dependable datasets is important. One helpful tool for this job is LabelImg [14]. It's an open-source tool that lets you mark objects in images quickly and accurately. LabelImg is well-liked because it's simple, effective, and used by both beginners and experts in image processing. It's made with Python and has a user interface based on the Qt library. Instead of using shapes with lots of sides, LabelImg uses rectangles, which makes it easy to use and accurate at the same time.

Acquiring and annotating the dataset was a critical initial step in our methodology. We meticulously sourced the field hockey dataset, ensuring it encompassed a diverse range of playing scenarios, team formations, and game dynamics. The FH_Dataset, comprising 2,532 frames with a resolution of 1280x720 pixels, was chosen as the foundation for our research. Each frame underwent meticulous annotation, where distinct labels were assigned to key elements within the field hockey match. These labels included player representations for both Team 1 (referred to as China) and Team 2 (referred to as England), the hockey ball, umpires, and goalies. This collection of labeled frames is referred to as FH_Dataset, as detailed in *table 1* [15].

Table 1. FH_Dataset

	Without Pre-processing (FH_Dataset)
Total Images	2532
Classes	5
Unannotated	0
Training Set	1791 (70%)
Validation Set	511 (20%)
Testing Set	252 (10%)
Annotation	24918 (9.8 per Image(Average)
Average Image Size	0.92 mp
Median Image Ration	1280x720
Class Instances	
1.China	11558(46.38%)
2. England	11087(44.49%)
3.Hockey_Ball	1259(5.05%)
4.Umpire	681(2.73%)
4.Goalies	331(1.32%)

Each annotation was carefully placed to accurately delineate the positions and movements of these entities within the frame. This annotation process ensured that the dataset captured the intricate dynamics of field hockey gameplay, laying the groundwork for robust model training and evaluation. The attention to detail in dataset acquisition and annotation was pivotal in facilitating the development of accurate and reliable object detection models tailored specifically for the field hockey domain.

2.2 YOLOv8 architecture & Model Training

YOLOv8 is a one-stage object detection model that predicts both objects bounding boxes and class labels simultaneously. It builds upon the YOLOv3 architecture, introducing various improvements such as a more efficient and accurate backbone network, an anchor-free approach in the head network for object detection, and a robust loss function designed to handle object occlusion and deformation more effectively [16]. *Figure 2* shows the custom object detection approach for Field hockey dataset.

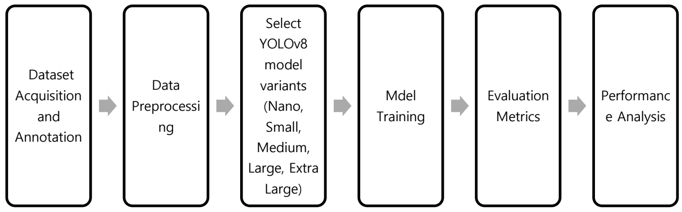

Figure 2. YOLOv8-based Object Detection for Field Hockey Analysis

YOLOv8, the latest iteration of the YOLO (You Only Look Once) object detection algorithm, was developed by Ultralytics and released in 2023[17]. Renowned for its state-of-the-art performance, YOLOv8 has demonstrated exceptional results on benchmark object detection datasets like COCO and VOC. Notably, it boasts impressive speed, achieving inference speeds of over 100 frames per second on a GPU. This versatile algorithm finds application across diverse domains such as autonomous driving, robotics, surveillance, retail, medical imaging, and agriculture. As an open-source tool, YOLOv8 has gained significant popularity in both research and developmental sectors, owing to its accessibility and adaptability. The architecture of YOLOv8 comprises two primary sections: the Backbone and Head. The backbone of the architecture consists of convolutional layers (abbreviated as 'Conv') followed by corresponding C2F layers. This sequential arrangement is designed to extract features from the input image, starting with general details and progressively focusing on finer nuances. The backbone also includes a Spatial Pyramid Pooling Feature (SPPF) module, contributing to feature extraction. As the depth of the backbone increases, there's a decrease in spatial dimensions but an increase in channel dimensions. The "Head" section, centered on the YOLOv8Head, refines features extracted by the Backbone for object detection. It consists of convolutional layers, concatenation, upsample operations, and "Detect" blocks. These layers enhance features to accurately predict bounding boxes, classification labels, and confidence scores for detected objects. Outputs include bounding box predictions ('Bbox'), class predictions ('Cls.'), and associated losses.

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YOLOv8 undergoes supervised learning, trained on image data paired with their respective ground truth labels. During training, the network minimizes the loss between its predictions and the ground truth labels. During inference, YOLOv8 processes input images to predict bounding boxes and object classes. It achieves this by extracting features from the image using the backbone and subsequently using these features in the neck and head of the network to predict bounding boxes and object classes.

This study leveraged a Python 3 backend running on a Google Compute Engine GPU for computationally intensive tasks. The development and execution environment were Google Colaboratory. Utilizing an object detection system, a YOLOv8-based model pre-trained by the COCO Dataset was employed (as depicted in *figure 2*). Various YOLOv8 model variants, including Nano, Small, Medium, Large, and Extra Large, were trained on an annotated dataset using GPU acceleration. Training parameters such as image size, patience, and batch size were fine-tuned for optimal model convergence and performance.

The model received video frames of hockey games as inputs, with the YOLOv8 model specifically fine-tuned for hockey object detection. Outputs were obtained through non-maximum suppression of bounding boxes based on the highest confidence score. Performance evaluation included standard metrics such as precision, recall, F-1 score, and overall accuracy (mAP@0.5), providing insights into the model's ability to detect and localize players, hockey balls, umpires, and goalies within field hockey frames. Model validation was conducted on a separate validation set comprising 20% of the annotated dataset, with additional assessment on a testing set accounting for 10% of the data, to evaluate generalization and robustness[18]. Comprehensive analysis of the results enabled the assessment of the effectiveness of the YOLOv8-based custom object detection approach for player detection in field hockey matches, with implications discussed for future research and real-world applications in sports analytics.

3. Result and Discussion

This section analyzes the performance of our YOLOv8-based player detection system in field hockey. We evaluate the model's accuracy in detecting players, balls, umpires, and goalies using metrics like precision, recall, F1-score, and overall accuracy. We then discuss how these results can be used for sports analytics in field hockey, such as performance analysis, strategy development, and player improvement. *Table 2* presents the performance of a YOLOv8 model trained on the FH_Dataset for detecting various objects in field hockey videos. The model was trained for 100 epochs using a GPU for faster processing and a custom batch size. Each epoch represents one cycle where the model sees the entire dataset. Additionally, training was stopped after 100 epochs to prevent overfitting. The table showcases the model's performance across four different model sizes: Nano, Small, Medium, and Large. These sizes refer to the memory footprint of the trained model, with larger models typically offering higher capacity and potentially better performance, but also requiring more computational resources. The evaluation involved 511 images from the dataset, where the model's accuracy was measured for different object categories (represented by "Class" in the table).

The evaluation metrics include Precision, Recall, F1-Score, and Overall Accuracy (mAP@0.5). Precision indicates the proportion of correctly identified objects out of all detections for a specific class, while Recall reflects the proportion of actual objects in the image that were correctly detected [19]. F1-Score balances these two measures, with a score closer to 1 indicating better performance [20]. Overall Accuracy, denoted by mAP@0.5, signifies the Mean Average Precision at an Intersection over Union (IoU) threshold of 0.5, wherein IoU quantifies the extent of overlap between a predicted bounding box and the actual object's position in the image, with a higher mAP indicating superior overall detection accuracy [19]. The table reveals promising results, with the model achieving an overall accuracy (mAP@0.5) of around 85% across all model sizes. However, some variations exist regarding performance and model size. The Medium model achieves the highest F1-score (0.849), followed by Large (0.847), Small (0.837), and Nano (0.841). This could be attributed to factors like model complexity. The Nano variant achieves an accuracy of 84.30%, while the accuracy increases progressively with model size, peaking at 85.70% for the Extra Large variant. Larger models, with more parameters, might have a higher capacity to learn complex features, leading to better detection accuracy. However, smaller models can be easier to train and require less computational power.

Another positive observation is that both Precision and Recall values are generally high, indicating the model makes relatively few false positives (incorrect detections) and misses fewer actual objects. However, depending on the application, the trade-off between precision and recall might be crucial. For instance, in player tracking, a high recall might be more critical to ensure all players are identified, even if it leads to a few false positives.

Table 2. Accuracy of YOLOv8 Model for FH_Dataset (Epochs: 100; Image Size: 640; Patience: 100; Device: GPU; Batch Size: Custom)

No. of epochs	YOLOv8 Model	Model Size (MB)	CLASS	Instances	Images	PRECISION	RECALL	F-1 SCORE	Overall Accuracy (mAP@0.5)
100	N (Nano)	5.9	ALL	4941	511	0.825	0.857	0.841	84.30%
	S (Small)	21.4	ALL	4941	511	0.802	0.875	0.837	84.80%
	M (Medium)	49.6	ALL	4941	511	0.832	0.867	0.849	85.50%
	L (Large)	83.6	ALL	4941	511	0.833	0.861	0.847	85.40%
	X	130.4	ALL	4941	511	0.832	0.861	0.846	85.70%

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Figure 3 shows simulation results of the YOLOv8x model on this dataset for 100 epochs. Training and validation loss are decreasing, indicating the model is learning [21]. Lower box_loss, cls_loss, and dfl_loss suggest good bounding box, classification, and unspecified task prediction. Precision and recall inching towards improvement in object classification. Finally, rising mAP50(B) and mAP50-95(B) indicate the model is getting better at identifying objects.

Table 3. Performance of YOLOv8x Model for FH_Dataset

No. of Epoch	Class	Images	Instances	PRECISION	RECALL	F-1 SCORE	Overall Accuracy (mAP@0.5)
100	China	511	2296	0.941	0.972	0.956	97.60%
	England	511	2210	0.929	0.967	0.948	97.40%
	Goalies	511	73	0.839	0.973	0.901	95.20%
	Hockey_Ball	511	237	0.648	0.468	0.543	51.10%
	Umpire	511	125	0.801	0.928	0.860	87.10%
	ALL	511	4941	0.832	0.861	0.846	85.70%

Table 3 displays the performance metrics of the YOLOv8x model for the FH_Dataset, indicating a model summary with 268 layers, 68,128,383 parameters, 0 gradients, and 257.4 GFLOPs. It presents the performance metrics of the YOLOv8x model for the FH_Dataset across various classes after 100 epochs. It indicates high precision and recall values for classes such as China and England, with F-1 scores of 0.956 and 0.948, respectively, contributing to an overall accuracy (mAP@0.5) of 97.60% and 97.40%. However, classes like Goalies and Hockey_Ball exhibit lower precision and recall values, resulting in relatively lower overall accuracies of 95.20% and 51.10%, respectively. Overall, the model achieves an average precision of 85.70% across all classes, demonstrating its effectiveness in detecting objects in the FH_Dataset.

In *figure 4*, the confusion matrix is depicted after the same training duration, serving as a tool to assess the performance of an image classification model. Each row represents the actual classes of the data, while each column represents the classes predicted by the model [22]. The matrix cells indicate the number of instances where the model predicted a specific class (column) for data actually belonging to a different class (row). The rows and columns are labeled with categories such as “China”, “England”, “Goalies”, “Hockey_Ball”, “Umpire”, and “background”. For example, the cell value at the intersection of the “China” row and “England” column indicates the number of times the model predicted “England” for an image actually containing “China”. In this matrix, most values lie on the diagonal, suggesting the model's strong performance. However, there are some exceptions, notably in distinguishing between “Goalies” and “Umpire”, and in misclassifying “background” images as “Hockey_Ball”. *Figure 5* illustrates the results of object detection using the YOLOv8x model at Epoch 100, with (a) to (d) showcasing input images and (e) to (h) displaying their corresponding output images.

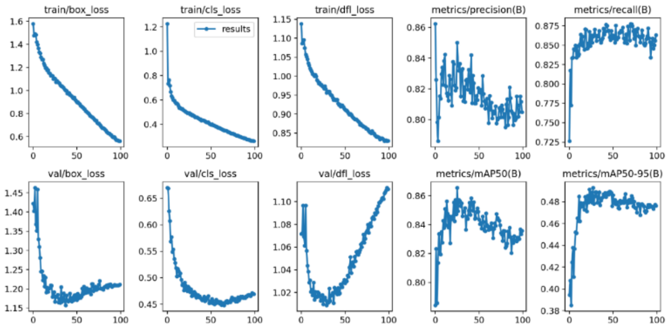

Figure 3. Simulation results obtained on YOLOv8x for FH_Dataset

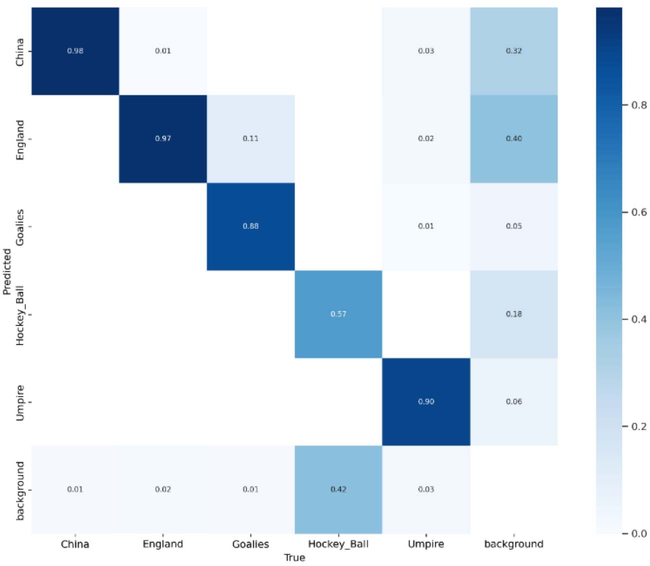

Figure 4. Confusion matrix of YOLOv8m Model for 100 Numbers of epoch

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(a)

(b)

(c)

(d)

(e)

(f)

(g)

(h)

Figure 5. Results of object detection Model: YOLOv8x Epoch:100, (a) to (d) Input Image, (e) to (h) Corresponding output image

6. CONCLUSIONS

In conclusion, this research presents a comprehensive investigation into the application of YOLOv8-based custom object detection for player detection in field hockey matches. Through extensive experimentation and evaluation, the effectiveness of the proposed approach in accurately detecting players amidst the dynamic gameplay and varying field conditions has been demonstrated. The study highlights the importance of dataset acquisition and annotation, showcasing the meticulous curation of the FH_Dataset and its role in training robust object detection models. The study evaluates the performance of the YOLOv8 model across various classes, including China (team 1), England (team 2), Hockey_Ball, Umpire, and Goalies, employing different model sizes and a fixed number of epochs. Evaluation metrics such as precision, recall, F1 score, and overall accuracy at a mean average precision (mAP) threshold of 0.5 are employed to assess model performance. The analysis reveals that increasing the model size generally enhances performance metrics across all classes. Notably, the YOLOv8x model size achieves the highest precision, recall, F1 score, and overall accuracy among the evaluated sizes. However, it's imperative to consider the trade-off between model performance and size, as larger models may necessitate more computational resources for training and deployment.

The systematic evaluation using metrics such as precision, recall, and F-1 score provides valuable insights into the models' capabilities and areas for improvement. Furthermore, the discussion on confusion matrices elucidates specific challenges and areas of refinement for future research endeavors. Overall, the findings underscore the potential of YOLOv8-based custom object detection as a game-changing tool for advancing performance analysis and strategic decision-making in the field hockey domain, paving the way for enhanced understanding and optimization of gameplay dynamics.

Supplementary Materials: The following are available online at www.forexjournal.co.in/download/sup.pdf, Figure S1: title, Table S1: title, Video S1: title.

Author Contributions:
Suhas H. Patel and Dipesh Kamdar conceptualized and designed the YOLOv8-based object detection framework for field hockey and developed the custom dataset and implemented data preprocessing. while Nileshkumar M. Bankar and Vijay Chavda optimized model hyperparameters and analyzed detection accuracy, with Nirajkumar K. Chaudhari contributing to literature review, result interpretation, and manuscript preparation. Together, their collaborative efforts led to the successful development and evaluation of the YOLOv8-based player detection system for field hockey.

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