Deep Learning-Based Futsal Field Segmentation: a Comparative Study of YOLOv8 and YOLO11-Pose Models*

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Abstract
Precise segmentation of futsal playing fields is essential for sports analytics, player tracking, and automated game analysis. This study introduces a YOLO-based approach using YOLOv8-Pose and YOLO11-Pose models for keypoint detection and field segmentation. A custom annotated dataset was developed and made publicly available, incorporating keypoints for essential field components. Data augmentation techniques, including brightness adjustment, exposure variation, and blurring, were applied to enhance model generalization. Experimental evaluations across S, L, and X model variants demonstrate that YOLO11-X achieved the highest segmentation accuracy with mAP50-95 of 0.947 and the lowest validation pose loss of 0.536. The loss convergence analysis confirms effective model optimization, with larger models exhibiting superior accuracy, while smaller models maintain higher efficiency for real-time applications. The results highlight the effectiveness of YOLO-based pose estimation in automated futsal field segmentation. Future research will focus on expanding the dataset, integrating player tracking, and optimizing models for real-time deployment.

Keywords
YOLOv8-Pose, YOLO11-Pose, futsal field segmentation, deep learning, sports analytics

1. Introduction

Futsal, a fast-paced variant of football played on a smaller indoor court, has gained significant popularity in sports analytics and artificial intelligence-driven research [1]. Accurate segmentation of futsal playing fields is essential for applications such as automated player tracking, tactical analysis [2], game event detection, and augmented reality-based sports broadcasting. Traditional methods for field segmentation rely on handcrafted feature extraction and conventional computer vision techniques [3], which often struggle with variations in lighting, occlusions, and camera angles.

Recent advancements in deep learning, particularly convolutional neural networks (CNNs) and object detection models, have revolutionized the field of sports analytics. The You Only Look Once (YOLO) framework has emerged as a state-of-the-art approach for real-time object detection and segmentation tasks. In this study, we leverage two advanced YOLO architectures—YOLOv8-Pose and YOLO11-Pose—to segment futsal playing fields effectively. These models utilize pose estimation capabilities, enabling precise detection of key field components such as boundary lines, goal areas, and center circles.

Our research aims to evaluate the performance of YOLOv8 and YOLO11 in futsal field segmentation by comparing their accuracy, efficiency, and robustness in real-world game scenarios. By analyzing multiple model variants (l, s, x), we assess their suitability for different computational

* IVUS2025: Information Society and University Studies 2025, May 15, Kaunas, Lithuania
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environments, from edge devices to high-performance servers. The key contributions of this study include:

- Creation of a custom futsal field keypoint dataset, providing annotated keypoints for field segmentation and pose estimation, publicly available on Roboflow;
- Implementation and evaluation of YOLOv8-Pose and YOLO11-Pose for futsal field segmentation, analyzing performance across different model sizes for real-time sports analytics.

The remainder of this paper is structured as follows: Section 2 reviews related work on field segmentation and deep learning models in sports analytics. Section 3 describes the proposed methodology, including dataset preparation, model architecture, and evaluation metrics. Section 4 presents experimental results and analysis, and discussions. Finally, Section 5 concludes the study with future research directions.

2. Related work

The segmentation of playing fields is a critical component in sports analytics, enabling applications such as player tracking, event detection, and automated game analysis. Recent advancements in deep learning, particularly object detection and pose estimation models, have significantly improved the accuracy and efficiency of field segmentation.

2.1. Traditional Approaches to Field Segmentation

Early methods for sports field segmentation relied on classical computer vision techniques, such as edge detection, color thresholding, and Hough transforms [4,5]. While effective under controlled conditions, these approaches struggled with real-world challenges like lighting variations, occlusions, and camera distortions.

2.2. Deep Learning for Sports Field Segmentation

Deep learning has revolutionized field segmentation by enabling automatic feature extraction and improved robustness across different conditions [6]-[8]. Fully Convolutional Networks (FCNs) and U-Net architectures have been widely used for sports field segmentation, demonstrating superior performance over traditional methods. Studies applying these models to soccer and basketball courts have shown significant improvements in boundary detection and field recognition.

Object detection models such as Faster R-CNN and YOLO have also been utilized for field segmentation, enabling real-time applications in sports broadcasting and tactical analysis. These models provide a balance between speed and accuracy, making them suitable for dynamic environments like futsal.

2.3. YOLO in Sports Analytics

The You Only Look Once (YOLO) framework has gained significant attention in sports analytics due to its real-time object detection capabilities [9]-[10]. Researchers have applied various versions of YOLO to tasks such as:

- Player tracking: Detecting and following players in soccer, basketball, and futsal matches [11]-[12].
- Ball detection: Identifying and tracking the ball's movement for automated event analysis [13]-[18].

- Event recognition: Recognizing key moments such as goals, fouls, and passes in real time [19]-[21].
- Pose estimation: YOLO-Pose models have been used to analyze player movements, helping in injury prevention and tactical assessments [22]-[23].

The recent advancements in YOLOv8 and YOLO11 extend these applications further by integrating segmentation and pose estimation, making them highly suitable for futsal field segmentation. These models can efficiently detect field boundaries, center lines, and goal areas while simultaneously tracking player positions.

2.4. Integration of Segmentation and Pose Estimation in Sports

Combining segmentation and pose estimation enhances sports analysis by simultaneously detecting field boundaries and tracking player positions. YOLOv8 and YOLO11 models offer multi-task learning capabilities, making them well-suited for real-time applications in futsal. Research in this area suggests that integrating segmentation with pose estimation improves tracking accuracy and game event detection.

2.5. Application to Futsal Field Segmentation

Despite extensive research on sports field segmentation, limited studies have specifically addressed futsal. Given the smaller playing area and dynamic nature of the game, accurate segmentation is essential for automated analysis. Our study evaluates the performance of YOLOv8-Pose and YOLO11-Pose models for futsal field segmentation, contributing to the advancement of AI-driven sports analytics.

3. Methodology

The methodology of this study focuses on detecting and segmenting futsal playing fields using YOLO-based deep learning models. The performance of these models is evaluated and compared using various metrics.

3.1. Dataset

In this work, we created a dedicated futsal field keypoints dataset, which has been made publicly available on the Roboflow platform [24]. This dataset consists of annotated futsal field images with carefully labeled keypoints, designed to enhance the accuracy of pose estimation and segmentation models. Each image includes structured keypoints that define field boundaries and centerline markers, ensuring comprehensive training for YOLOv8-Pose and YOLO11-Pose models. Table 1 presents an overview of the dataset.

Table 1
Details of used dataset

Input frame	Train	Validation	Test	Total
1080x1080	115	33	16	164

Figure 1 presents a set of randomly selected training images for futsal field keypoints annotation.

Figure 1: Samples from original images used in the dataset.

3.2. Preprocessing and Data Augmentation

To enhance the robustness and generalization of our Futsal Field Keypoints Dataset, we applied various data augmentation techniques to simulate different real-world conditions. These augmentations help the model adapt to lighting variations, color shifts, and minor distortions, improving its accuracy in diverse futsal environments. Specifically, 15% of images were converted to grayscale, ensuring that the model does not overly rely on color information for keypoint detection. Hue adjustments within a ±15° range and saturation variations between -25% and +25% were applied to account for different court surface colors and lighting conditions. Additionally, brightness was adjusted within a ±15% range, and exposure varied between -10% and +10%, helping the model handle shadows and varying indoor lighting conditions commonly found in futsal arenas.

To further enhance the dataset, we introduced slight Gaussian blur (up to 0.6px) to simulate motion blur and camera focus variations, which are common in fast-paced sports environments. These augmentations were carefully chosen to maintain keypoint integrity while improving model adaptability across different camera angles and lighting setups. By incorporating these variations, our dataset ensures that YOLOv8-Pose and YOLO11-Pose models can generalize effectively, leading to improved performance in real-time futsal field segmentation, tracking, and sports analytics applications. Table 2 and Figure 2 present an overview of the used dataset after data augmentation.

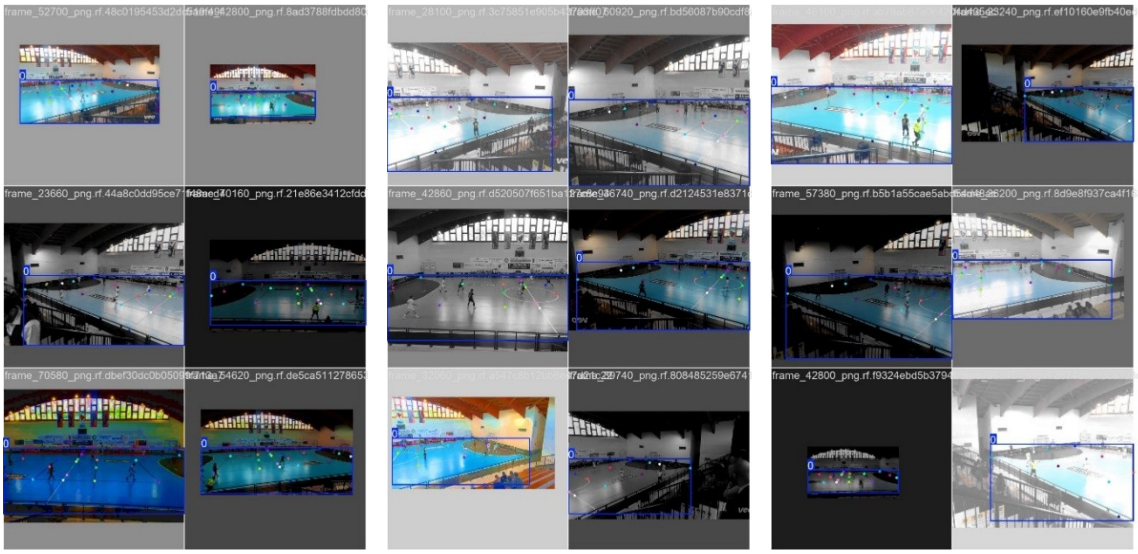

Figure 2: Samples from the dataset after data augmentation.

Table 2
Details of used dataset after data augmentation

Input frame	Train	Validation	Test	Total
1080x1080	345	33	16	394

3.3. Applied YOLO Models for Futsal Field Segmentation

In this work, we used YOLOv8-Pose and YOLO11-Pose models, which are advanced deep learning architectures designed for real-time object detection, pose estimation, and segmentation. YOLOv8-Pose includes three key variants—Small (S), Large (L), and Extra Large (X)—each offering a balance between speed and accuracy. YOLOv8-S, which we used for real-time futsal field segmentation, is optimized for speed and suitable for edge devices, though it has slightly lower accuracy. YOLOv8-L, which we employed for detailed field boundary detection, provides a balance between computational efficiency and segmentation precision. On the other hand, YOLOv8-X, which we utilized for high-resolution futsal analytics, delivers the highest accuracy, capturing intricate field and player keypoints with minimal error, making it ideal for detailed segmentation and tracking.

Similarly, in this work, we used YOLO11-Pose models, which improve upon their predecessors with enhanced pose estimation and segmentation capabilities. YOLO11-S, used for real-time futsal field segmentation and player tracking, prioritizes speed and is particularly effective in automated sports cameras and AI-powered refereeing systems. YOLO11-L, which we applied for field detection with moderate computational resources, balances processing speed and segmentation accuracy. YOLO11-X, the most powerful model we employed, excels in high-precision segmentation, offering detailed keypoint tracking for professional futsal analysis. Both YOLOv8 and YOLO11 models, as used in our study, provide scalable solutions depending on computational power, with smaller models (S) suited for real-time applications and larger models (X) optimized for high-fidelity sports analytics.

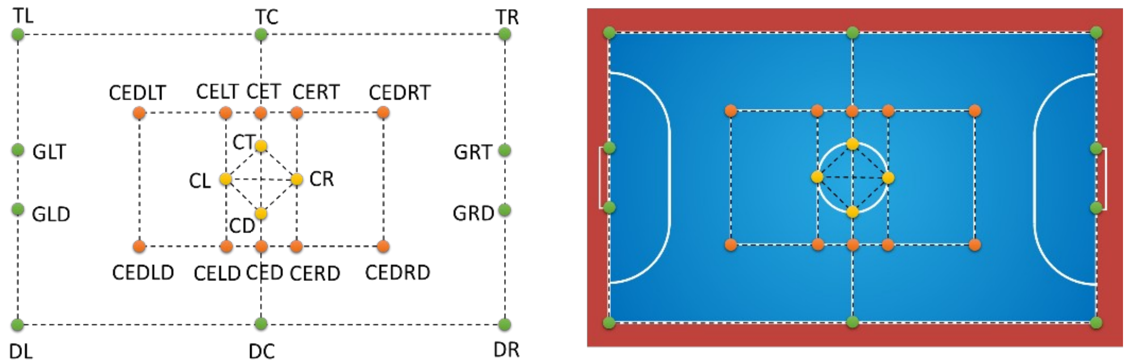

Figure 3: Proposed keypoint annotation method.

The proposed keypoint annotation method defines a structured set of keypoints to enhance the accuracy of pose estimation and field segmentation. These keypoints are strategically placed to represent essential field components, aiding in real-time detection and analysis. As shown in Figure 3, the keypoints are categorized into three main groups: field boundary keypoints (green), which outline the outer limits of the futsal field and goal areas (TL: Top Left, DL: Down Left, TR: Top Right, DR: Down Right, GLT: Goal Left Top, GLD: Goal Left Down, GRT: Goal Right Top, GRD: Goal Right Down); central and structural keypoints (orange), which define critical zones such as the penalty area, center circle, and goal regions (CET: Center Edge Top, CED: Center Edge Down, CELT: Center Edge Left Top, CERT: Center Edge Right Top, CELD: Center Edge Left Down, CERD: Center Edge Right Down, CTR: Center Right, CTL: Center Left, CT: Center Top, CD: Center Down); and inner field grid points (yellow), which provide additional reference markers for improved segmentation accuracy (CEDLT: Center Edge Double Left Top, CEDRT: Center Edge Double Right Top, CEDLD: Center Edge Double Left Down, CEDRD: Center Edge Double Right Down). By systematically distributing these keypoints, the model ensures that key futsal field elements are detected with precision, reducing errors caused by camera distortions or lighting variations.

This structured annotation method is essential for training YOLO-Pose models (YOLOv8 and YOLO11) for futsal field segmentation. The inclusion of goal positions, field edges, and center line markers allows the models to better understand field structures, improving the segmentation process across various perspectives. The proposed method also ensures consistency in detection, making it robust for real-time futsal analytics applications, including automated game tracking, tactical analysis, and referee assistance systems. By integrating this keypoint mapping approach, the segmentation model achieves higher accuracy and reliability, making it a valuable tool in AI-powered sports analytics.

3.4. Evaluation metrics

The evaluation metrics employed in this study include L_{pose}, mAP_{50}^{pose} and mAP_{50-95}^{pose}. The performance evaluation is conducted using the following equations:

$$L_{pose}=\frac{1}{N}\sum_{i=1}^{N}\left\|\widehat{P}_i-P_i\right\|^2, \tag{1}$$

where
N - total number of keypoints per sample;
$\widehat{P}_i$ - $(x_i^{pred},\ \ y_i^{pred})$ is the predicted keypoint position;
P_i - $(x_i^{gt},\ \ y_i^{gt})$ is the ground-truth keypoint position.

$$mAP_{50}^{pose}=AP(OKS\geq 0.50), \tag{2}$$

where
OKS - Object Keypoint Similarity;
AP - Average Precision.
OKS and AP are calculated using the following equations:

$$OKS=\frac{\sum_i \exp\left(-\frac{d_i^2}{2s^2k_i^2}\right)\delta\ (v_i>0)}{\sum_i \delta(v_i>0)}, \tag{3}$$

where
d_i - Euclidean distance between predicted keypoint $\widehat{K}_i$ and ground truth K_i;
s - object scale (bounding box size or reference distance);
k_i - keypoint-specific normalization factor;
v_i - visibility flag (1 if visible, 0 otherwise).

$$AP(50)=\int_0^1 P(r)\,dr, \tag{4}$$

where
$P(r)$ - precision at recall level r.

$$mAP_{50-95}^{pose}=\frac{1}{10}\sum_{0.50}^{0.95} AP(t), \tag{5}$$

where
$t\in\{0.50,\ 0.55,\ 0.60,\ \ldots,\ 0.95\}$ (10 values).

4. Results and Discussion

The training process for our YOLOv8-Pose and YOLO11-Pose models was conducted using the following hardware specifications: an Intel Core i7-14700K CPU, 32GB of RAM, and an NVIDIA RTX 4080 GPU with 16GB. These specifications provided sufficient computational power to handle large-scale training while ensuring efficient model optimization.

The training was carried out for 400 epochs with a batch size of 8, allowing the model to learn keypoint relationships, refine segmentation accuracy, and enhance field detection performance. The high memory capacity and powerful GPU facilitated batch processing and real-time augmentation, ensuring that the model generalizes well across different lighting conditions and camera perspectives. This setup enabled us to train high-resolution futsal field segmentation models efficiently while maintaining high precision in keypoint detection and pose estimation.

The experimental results illustrating the training and testing behavior of the used models are presented in Table 3.

Table 3
Evaluation metrics for YOLOv8-Pose and YOLO11-Pose on futsal field segmentation

№	Model name	Size	mAP^{pose} 50 - 95	Val/pose_loss	FPS
1		S	0.840	1.208	41.071
2	YOLOv8[s]-Pose	L	0.873	1.031	13.463
3		X	0.905	0.778	9.303
4		S	0.907	0.770	43.926
5	YOLO11[s]-Pose	L	0.940	0.566	17.389
6		X	0.947	0.536	10.416

Table 3 presents a comparative evaluation of YOLOv8-Pose and YOLO11-Pose models for futsal field segmentation, using mean Average Precision (mAP50-95) and validation pose loss as key performance metrics. The mAP50-95 metric quantifies the model's accuracy in detecting keypoints across multiple IoU thresholds, while validation pose loss represents the model's error in keypoint localization during validation. A higher mAP50-95 value indicates superior segmentation accuracy, whereas a lower validation pose loss suggests better convergence and reduced keypoint prediction errors. The table further categorizes results based on model size (S, L, X), which determines the trade-off between computational efficiency and predictive performance.

Building on the robust foundation of YOLOv8, YOLO11 introduces further architectural refinements, with a particular focus on optimizing the backbone, neck, and head structures to reduce parameters and computational cost (FLOPs) while simultaneously enhancing performance. Moreover, the research was carried out with limited hardware resources compared to those typically required for high-resolution keypoint detection tasks. Consequently, the results demonstrate that YOLO11-Pose outperforms YOLOv8-Pose across all model sizes, exhibiting consistently higher mAP50-95 values and lower validation pose loss. Notably, the YOLO11-X model achieves the highest mAP score (0.947) and the lowest pose loss (0.536), indicating superior keypoint detection accuracy and enhanced generalization. The YOLO11-L model also performs competitively, achieving a high mAP50-95 (0.940) with a pose loss of 0.566, further supporting the robustness of the YOLO11-Pose architecture. Conversely, the YOLOv8-Pose models exhibit relatively higher validation pose loss values, which suggests reduced localization precision compared to their YOLO11-Pose counterparts.

A clear correlation is observed between model size and performance, where larger models (X variants) consistently achieve higher accuracy and lower pose loss, while smaller models (S variants) maintain moderate accuracy with improved computational efficiency. These findings indicate that YOLO11-X is the most suitable model for real-time futsal field segmentation, as it provides the highest accuracy while minimizing keypoint localization errors. The study highlights the effectiveness of YOLO-based pose estimation models in sports analytics, reinforcing their potential for applications in automated referee systems, player tracking, and tactical analysis.

The performance evaluation of the YOLO11-X model for futsal field segmentation is presented in Figure 4.

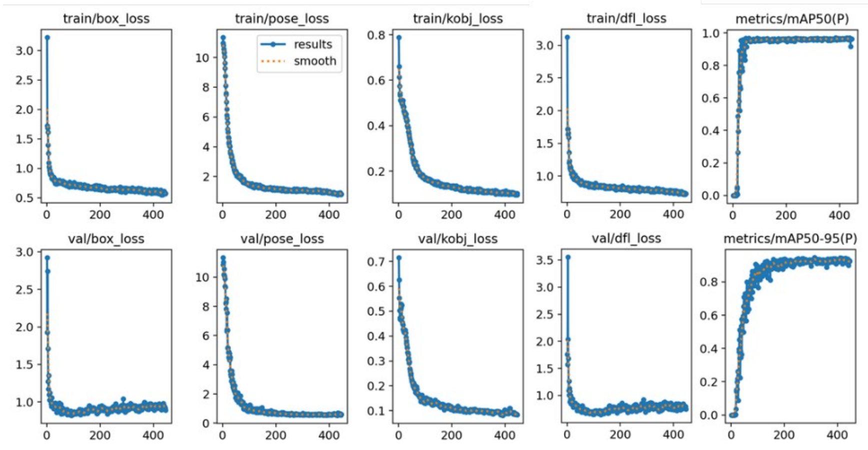

Figure 4: Performance evaluation of the YOLO11-X model for futsal field segmentation.

Figure 4 presents the training and validation performance metrics of the YOLO11-X model for futsal field segmentation over 400 epochs. The top row displays training loss curves, while the bottom row shows validation loss curves and accuracy metrics. The box loss decreases rapidly, indicating improved field boundary detection, while the pose loss stabilizes after early epochs, showing effective keypoint learning. The keypoint objectness loss steadily declines, confirming improved confidence in detected keypoints, and the distribution focal loss reduces sharply, suggesting precise keypoint alignment. The mAP50(P) metric stabilizes near 0.98, demonstrating strong accuracy in keypoint detection, while mAP50-95(P) exceeds 0.90, confirming the model's robustness across different levels of precision evaluation. These results indicate effective loss convergence, reduced error rates, and high segmentation accuracy, making YOLO11-X highly suitable for real-time futsal field analysis.

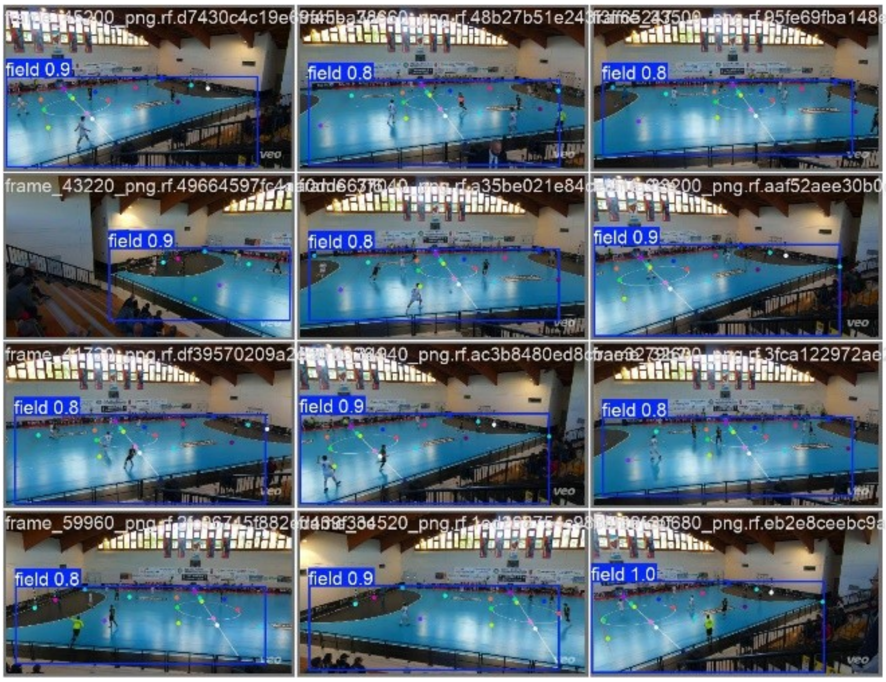

Figure 5: Predicted keypoint detection results on the validation set.

5. Conclusion

This study presented a comprehensive evaluation of YOLOv8-Pose and YOLO11-Pose models for futsal field segmentation and keypoint detection, with a particular focus on model accuracy, loss convergence, and real-time applicability. A custom futsal field keypoint dataset was developed and publicly shared to facilitate further research in pose estimation and sports analytics. Through rigorous experimentation, results demonstrated that YOLO11-X outperformed all other models, achieving the highest mAP50-95 (0.947) and the lowest validation pose loss (0.536), confirming its superior accuracy and robustness.

The loss convergence analysis showed that all models successfully learned keypoint relationships, with YOLO11-X exhibiting the best optimization stability. The results indicate that larger models (X variants) provide higher segmentation accuracy, while smaller models (S variants) offer better computational efficiency for real-time applications. These findings highlight the potential of YOLO-based pose estimation models in automated futsal analytics, tactical analysis, and referee assistance systems.

Future work will focus on expanding the dataset with more diverse game environments, integrating temporal tracking for dynamic player-field interactions, and optimizing the models for low-power edge devices to enhance real-world deployment. More than 5000 images will be annotated from different angles of view, color, and lighting conditions. The findings of this study contribute to the advancement of AI-driven sports analytics, paving the way for more accurate and efficient futsal field segmentation and tracking applications.

Declaration on Generative AI

The authors have not employed any Generative AI tools.

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