

AI-Driven Post-Game Scrabble Analysis for Rule-Violation Detection and Classification

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A B S T R A C T

This study presents an Artificial Intelligence (AI)-based computer vision approach for automated post-game detection of rule violations in physical Scrabble gameplay. Manual identification of incorrect tile placements can be time-consuming and dependent on player or expert judgment, creating a need for an automated method that can analyze board images consistently. The proposed approach uses a YOLO-based object detection model to identify and localize rule-violating tile placements on a standard 15×15 Scrabble board. A custom dataset of 1,500 annotated images was developed, containing five categories of rule violations: incorrect initialization, insufficient tile count, non-linear placement, lack of connectivity, and invalid adjacency. Each violation category was treated as a separate detection class, with bounding-box annotations used to identify the locations of incorrect placements. YOLOv8, YOLOv9, and YOLOv10 models were trained and experimentally compared to determine the most suitable model for rule-violation detection. Among the evaluated models, YOLOv9 achieved the strongest performance, obtaining a precision of 97.99%, recall of 98.51%, mAP@50 of 99.00%, and mAP@50–95 of 91.21%. These results demonstrate the effectiveness of the YOLO-based approach in detecting and localizing predefined Scrabble rule violations from board images. The proposed system provides visually interpretable post-game feedback through bounding boxes, supporting automated and consistent review of rule adherence in physical Scrabble gameplay.

Keywords: Computer Vision, Deep Learning, YOLOv8, YOLOv9, YOLOv10, YOLO- based, post- game

1. Introduction

Scrabble is recognized as a word-based board game. It challenges players to form words on a game board using letter tiles (Aung *et al.*, 2021). Although Sri Lanka has the Sri Lanka Scrabble League (SLSL) and newer clubs such as the Western Scrabble League, the overall player base and number of competitions remain small compared to international standards. This situation

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highlights a critical gap in the availability of high-quality coaching. Therefore, many young players may have limited opportunities for skill development. Although computer vision-based tile recognition and deep Learning-based move evaluation in Scrabble games have been explored as individual components, there is currently no formally documented end-to-end system that integrates these components into a unified pipeline for analyzing physical Scrabble gameplay (Abraham, 2017; Jha, 2025). Furthermore, there is no existing automated coaching functionality for checking whether tile placements adhere to Scrabble rules (Jha, 2025). Such a system has the potential to improve access to elite-level training and significantly reduce barriers to measurable skill development. To check whether players adhere to Scrabble rules or not, this study implements a YOLO-based deep learning feedback system. The system does not analyze player-based behavioral patterns, empty tiles, or the private racks of tiles during the Scrabble game. The performance of this system depends on the quality of the captured board images, such as lighting conditions and image clarity. Furthermore, this system is designed to analyze only the standard original Scrabble board.

The main objective of this study is to develop a computer vision-based deep learning system for detecting predefined rule violations in physical Scrabble gameplay. As the system evaluates five predefined Scrabble rules, the study involves collecting a dataset of rule-violating tile placements (Edley & Williams, 2009). These include the following five rules.

Rule 1 – Initialization

The opening move must be placed horizontally or vertically, with at least one tile covering the center square.

Rule 2 – Minimum Count

The first move must consist of two or more tiles forming a valid word.

Rule 3 – Linearity

Diagonal word formation is not permitted; all tiles played in a turn must align along a single row or column.

Rule 4 – Connectivity

All new tiles must connect to the existing board structure; isolated placements are prohibited.

Rule 5 – Adjacency

Newly played tiles must be adjacent to existing letters in either an orthogonally connected row or column, ensuring a unified board structure.

1.1 Research Problem

The fundamental shortcomings of current tools and traditional methods for Scrabble game analysis constitute a significant problem in the assessment of rule adherence. These approaches frequently lack integration with physical gameplay, making the assessment process time-consuming and dependent on manual inspection. Existing research on physical Scrabble gameplay has primarily focused on board recognition, tile identification, and scoring rather than the automated detection of rule violations from physical board images (He & Witzel, 2022; Jha, 2025). Consequently, the analysis of physical Scrabble games for rule adherence assessment remains primarily a manual process.

As Scrabble rules must be applied accurately and consistently throughout gameplay, maintaining rule adherence remains a challenge, particularly for beginner players. In the context of physical Scrabble boards, there is a lack of an automated mechanism for identifying

incorrect tile placements and determining whether predefined rules have been violated. The absence of such a mechanism limits the ability to provide objective and consistent feedback on rule adherence. Furthermore, manual assessment can be difficult to perform consistently and efficiently. Therefore, there is a need for a system that can automatically analyze physical Scrabble board images and identify predefined rule violations. This study addresses this problem by proposing a YOLO-based deep learning system for detecting and localizing rule violations from images of physical Scrabble boards.

2. Review of Literature

Computer vision and deep learning have increasingly been applied to interpret physical board games by converting visual information from game boards into machine-readable representations. In the context of Scrabble, He and Witzel developed computer-vision methods for recognizing physical Scrabble board states using image-processing techniques and convolutional neural networks (CNNs). Their approach identified individual tile types and reconstructed the corresponding digital board state, demonstrating the feasibility of applying computer vision to physical Scrabble gameplay. Their results achieved an accuracy of 93.10% for Scrabble board recognition, providing a foundation for automated interpretation of physical Scrabble boards (He & Witzel, 2022).

Further work has investigated the use of artificial intelligence for automated analysis of real-world Scrabble gameplay. Jha (2025) developed an AI-enabled Scrabble scoring system using computer vision and deep learning. The system employed DeepLabv3 for board segmentation and EfficientNet-Bo for identifying individual tile characters and tracking newly placed tiles. It also applied Scrabble rules to calculate scores for different gameplay situations. This study demonstrates the applicability of deep learning to physical Scrabble board analysis. However, its primary focus was automated scoring rather than the visual detection and localization of predefined rule violations (Jha, 2025).

The importance of rule adherence and fairness in Scrabble has also been investigated from a computational perspective. Aung et al. (2021) examined fairness in Scrabble and discussed computational approaches for providing feedback during gameplay. Their work demonstrates that computational analysis can support fair gameplay and player feedback. However, the study primarily addressed fairness and gameplay-related considerations rather than identifying incorrect tile placements from physical board images. Therefore, a distinction remains between computational assessment of gameplay fairness and visual detection of specific rule violations on physical Scrabble boards (Aung et al., 2021).

Beyond Scrabble, deep learning and object detection have been applied to identify spatially defined conditions in other visual domains. Wang et al. (2023) investigated maize stand counting and plant-spacing variability using UAV imagery and YOLO-based object detection models. Their annotation procedure involved manually drawing rectangular bounding boxes around target regions, including spacing variations such as skips and large gaps. The study demonstrates how bounding-box-based object detection can be used to localize spatial irregularities and gap-related conditions within structured visual scenes (Wang et al., 2023). Although the agricultural context differs from physical Scrabble gameplay, this methodology is relevant to the present study because some Scrabble rule violations are also determined by the spatial relationships and gaps between tiles. Therefore, the study was considered as a methodological reference for designing the annotation and bounding-box localization approach used to identify regions associated with incorrect tile placements and spacing-related rule violations.

Deep learning has also been investigated for automated verification of rules and structured states in other domains. Held et al. (2023) developed the Video Assistant Referee System (VARs), which applied video-based deep learning to support automated decision-making related to rule infractions in soccer. Similarly, Yarmohammadi et al. (2023) investigated deep-learning-based recognition of chessboard configurations and demonstrated the applicability of object detection techniques to structured board environments. These studies indicate that deep learning can support automated analysis when the spatial arrangement and position of objects are important for determining the state of a system (Held et al., 2023; Yarmohammadi et al., 2023).

Overall, previous research demonstrates several relevant areas of development. First, computer vision has been applied to the recognition and digital representation of physical Scrabble boards (He & Witzel, 2022; Jha, 2025). Second, research in other visual domains has demonstrated the use of YOLO-based object detection and bounding-box annotation for localizing spatially defined objects and irregularities (Wang et al., 2023). Third, deep learning has been applied to automated rule-related decision-making and structured board-state recognition in other domains (Held et al., 2023; Yarmohammadi et al., 2023). These studies provide methodological support for applying object detection to physical Scrabble board analysis.

However, existing Scrabble-related studies primarily focus on board recognition, tile recognition, scoring, or general gameplay analysis rather than directly detecting and localizing predefined rule violations from physical Scrabble board images. In particular, limited research has investigated the use of YOLO-based object detection to distinguish multiple predefined categories of Scrabble rule violations within a single detection framework.

Therefore, a research gap remains in the automated visual identification and localization of specific rule-violating tile placements in physical Scrabble gameplay. The present study addresses this gap by developing and comparatively evaluating YOLOv8, YOLOv9, and YOLOv10 for detecting and localizing five predefined categories of Scrabble rule violations which are incorrect initialization (Rule 1), insufficient tile count (Rule 2), non-linear placement (Rule 3), lack of connectivity (Rule 4), and invalid adjacency (Rule 5).

3. Methodology

This study employed a YOLO-based object detection model to identify and localize rule-violating tile placements on a physical Scrabble board. Each type of rule violation was treated as a distinct detection class during model training. The YOLO model generates bounding boxes around the violating tile placements, enabling their precise localization and visual interpretation. The detected placements were evaluated against the predefined Scrabble rules to determine whether they represented rule violations. By offering clear visual feedback through bounding boxes, the system helps players understand their mistakes and improve rule adherence through detailed post-game review.

Developing YOLO-based deep learning models for rule-violation detection was conducted in multiple stages. The first stage involved data collection, which was critical to ensuring that the deep learning models were trained on a diverse and representative dataset. After identifying incorrect tile placements on a physical Scrabble board according to the official Scrabble rules, players were instructed to intentionally make non-standard tile placements to simulate irregularities commonly observed among beginner players based on fundamental tile placement constraints. The dataset consisted of 1,500 images depicting rule violations, with each type of rule violation treated as a separate detection class. Each class comprised 300 images to maintain class balance and minimize potential bias toward any particular class. The

entire dataset was divided into three subsets, with 70% of the images allocated to the training set, 20% allocated to the validation set, and the remaining 10% allocated to the testing set. Each detection class was represented in all three subsets to ensure consistent class representation during model development and evaluation, thereby reducing the potential for class distribution bias and supporting a more reliable assessment of the model's detection performance.

Subsequently, a preprocessing step was performed to prepare the dataset for YOLO-based object detection model training. The preprocessing stage focused on enhancing board-level visibility and reducing irrelevant visual noise. Each image was cropped to include only the visible Scrabble board area. Following preprocessing, images were annotated using the LabelImg tool, a widely used open-source graphical image annotation tool. Bounding boxes were manually drawn to mark the positions of incorrect tile placements that violated the rules on the Scrabble board. During the annotation process, specific class labels were assigned to the five predefined rule-violation categories. Rule 1 (Initialization) was labelled as Center Not Covered, Rule 2 (Minimum Count) was labelled as Insufficient First Move, Rule 3 (Linearity) was labelled as Diagonal Placement, Rule 4 (Connectivity) was labelled as Isolated Placement, and Rule 5 (Adjacency) was labelled as Not Adjacent Placement. The annotation strategy was designed according to the specific characteristics of each rule violation. In cases where Rule 1 was violated, the center square of the Scrabble board was marked with a bounding box, as this rule requires the first word to cover the center star. For violations of Rule 2, where the word-length requirement was not satisfied, the entire Scrabble board was marked with a single bounding box. For violations of Rules 3, 4, and 5, the specific location where the rule was violated was marked with a bounding box around the incorrectly placed tiles. This annotation approach enables users to easily identify the source of the violation during the feedback stage.

Data augmentation using the Ultralytics YOLO framework was applied directly to the training process. This step was applied to the dataset to improve the diversity of the training data. Flipping, scaling, Hue, Saturation, and Value (HSV) adjustments, and blurring were used to improve robustness, while Contrast Limited Adaptive Histogram Equalization (CLAHE) enhanced contrast. Mosaic and blending were disabled to preserve the spatial relationships between tiles and their corresponding board positions.

Three YOLO-based object detection deep learning models, namely YOLOv8, YOLOv9, and YOLOv10, were developed for detecting rule violations using Google Colab. The YOLO family was selected because of its single-stage object detection architecture, which enables simultaneous object localization and classification in a single forward pass. These characteristics make YOLO suitable for post-game analysis of physical Scrabble board images. Since these models were required to detect small tile placements on the Scrabble board, each model was trained using the small variant. Small models offer faster training and inference times and are better suited to resource-constrained environments. They also provide an appropriate balance between computational efficiency and model capacity for the domain-specific task of rule-violation detection in board games.

Model development began with YOLOv8, while earlier YOLO versions were excluded from the study. This decision was based on several factors. YOLOv8 introduced significant architectural improvements, including anchor-free detection, an optimized loss function, and a stable and user-friendly training framework.

All YOLO-based small variant models were trained using the Ultralytics framework, which enabled data augmentation to be applied directly during the training process to enhance dataset diversity. To achieve optimal performance, they were trained with carefully selected

hyperparameters. These models were initialized with pretrained YOLO weights and trained for 50 epochs. An image size of 640×640 pixels and a batch size of 2 were used during the training process. Training was performed on a custom Scrabble dataset defined in a YAML configuration file. To balance computational efficiency and memory constraints, a single Graphics Processing Unit (GPU) with two data-loader workers was used.

4. Data Analysis and Findings

Different YOLO versions were experimentally evaluated to compare their performance in detecting predefined rule violations on physical Scrabble board images. The performance of the YOLO-based rule-violation detection models was assessed using precision, recall, F1-score, and mean average precision (mAP). These metrics were used to evaluate the models' ability to correctly identify and localize the predefined rule-violation categories in the testing dataset.

The experimental results showed that YOLOv9 achieved the highest overall performance among the evaluated models based on the reported detection metrics. The model obtained a precision of 97.99%, recall of 98.51%, F1-score of approximately 98.25%, mAP@50 of 99.00%, and mAP@50-95 of 91.21%. These results indicate strong detection and localization performance for the predefined rule-violation categories represented in the testing dataset. Table 1 presents the quantitative performance comparison of YOLOv8, YOLOv9, and YOLOv10 at epoch 50.

Table 1: Quantitative Performance Comparison of YOLO Versions Rule Violation Detection

Metric	YOLOv8	YOLOv9	YOLOv10
Precision	0.9118	0.9799	0.9566
Recall	0.9718	0.9851	0.9572
F1-Score (Approximately)	≈ 0.94	≈ 0.98	≈ 0.96
mAP@50	0.9710	0.9900	0.9830
mAP@50-95	0.7142	0.9121	0.8961

To further evaluate the class-wise detection performance of the YOLOv9 model, a confusion matrix was generated using the testing dataset. The confusion matrix illustrates the distribution of correct and incorrect detections across the five predefined rule-violation categories.

The background category shown in the confusion matrix represents background associated predictions in the object detection evaluation and is not treated as one of the five predefined rule violation classes. Most detections are concentrated along the diagonal, indicating correct classification of the predefined rule violation categories. The model correctly classified the five predefined categories which are Center Not Covered, Insufficient First Move, Diagonal Placement, Isolated Placement, and Not Adjacent Placement, with limited confusion between the categories. The occurrences associated with the background category represent background related detection outcomes in the object detection evaluation.

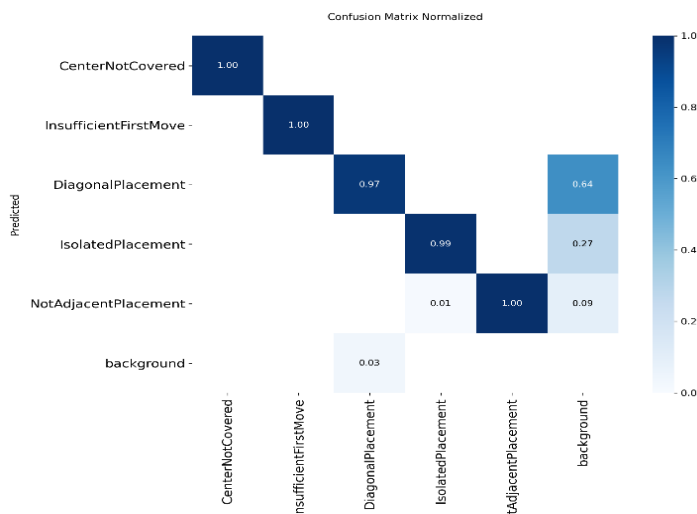


Figure 1: Normalized Confusion Matrix of YOLOv9 for Rule-Violation Detection

Representative prediction examples were examined to provide qualitative evidence of the model's detection performance. Figure 2 and Figure 3 present two examples of incorrect predictions in which rule violations were present on the board.



Figure 2: Insufficient First Move predicted while Center Not Covered was not detected



Figure 3: Center Not Covered predicted while Insufficient First Move was not detected

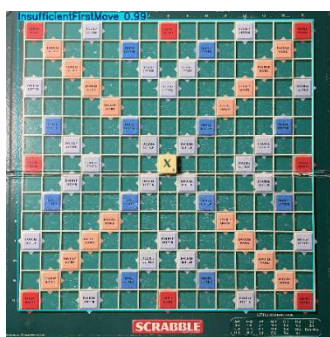


Figure 4: Insufficient First Move violation

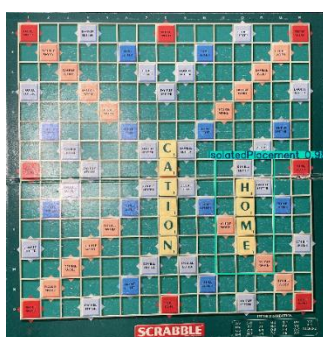


Figure 5: Isolated placement violation

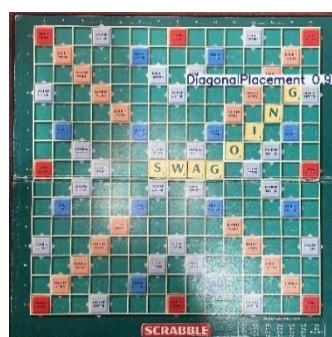


Figure 6: Diagonal placement violation



Figure 7: Not Adjacent Placement Violation

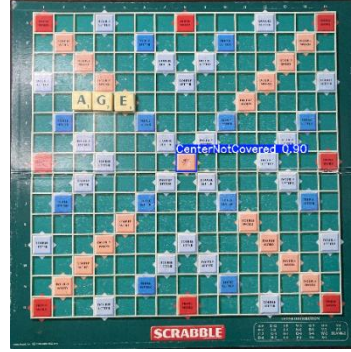


Figure 8: Center not covered violation

In Figure 2, the board contains both an Insufficient First Move violation, corresponding to Rule 2 (Minimum Count), and a Center Not Covered violation, corresponding to Rule 1 (Initialization). However, the model detected only the Insufficient First Move violation and failed to detect the Center Not Covered violation. In Figure 3, both Insufficient First Move and Center Not Covered violations are present, but the model detected only the Center Not Covered violation. These examples indicate that the model may not identify all applicable rule violations when multiple violations occur within the same board image, particularly when different violation types occur simultaneously.

Figures 4–8 present representative examples of correct YOLOv9 predictions for the five predefined rule-violation categories. Figure 4 shows a correctly detected Insufficient First Move violation (Rule 2), while Figure 5 presents a correctly detected Isolated Placement violation (Rule 4). Figure 6 illustrates a correctly detected Diagonal Placement violation (Rule 3), and Figure 7 shows a correctly detected Not Adjacent Placement violation (Rule 5). Figure 8 presents a correctly detected Center Not Covered violation (Rule 1). In each figure, the bounding box indicates the region correctly localized by YOLOv9 as containing the corresponding rule violation.

4.1. Precision

Precision measures the model's ability to correctly identify rule violations among all detected violations. It is calculated based on True Positives (TP), which represent correctly detected rule violations, and False Positives (FP), which represent legal tile placements incorrectly classified as rule violations. The YOLOv9 model achieved a precision of 97.99%. This demonstrates that the model was highly accurate in distinguishing actual Scrabble rule violations from legal tile placements. The high precision indicates that most of the placements identified by the model as rule violations were correctly classified as violations.

$$Precision = \frac{TP}{TP + FP}$$

4.2. Recall

Recall measures the model's ability to correctly identify actual Scrabble rule violations and minimize missed detections. It is calculated based on True Positives (TP), which represent rule violations that were correctly detected, and False Negatives (FN), which represent actual rule violations that were incorrectly missed by the model. The YOLOv9 model achieved a recall of 98.51%, demonstrating its strong capability to detect nearly all actual rule violations present in

the testing dataset. A high recall value shows that the system is sensitive to rule violations and rarely fails to detect them.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

4.3. F1-Score

The F1-score represents the harmonic mean of Precision and Recall. It provides a balanced measure of the model's performance when both correctly detecting violations and minimizing false detections are important. A higher F1-score indicates a better balance between Precision and Recall. For YOLOv9, using a Precision of 0.9799 and a Recall of 0.9851, the F1-score can be calculated as,

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Therefore, the YOLOv9 model achieved an F1-score of approximately 98.25%. This high value demonstrates that the model maintained a strong balance between identifying actual rule violations and avoiding incorrect detections. Thus, YOLOv9 can be considered highly reliable for the rule-violation detection task.

4.4. Mean Average Precision at IoU 0.50 (mAP@50)

Where N represents the number of detection classes, and AP_i represents the Average Precision (AP) of the i -th detection class at an Intersection over Union (IoU) threshold of 0.50. The mAP@50 value represents the mean detection performance across all detection classes at the 0.50 IoU threshold. A higher mAP@50 value indicates that the model can accurately detect and localize rule violations when a predicted bounding box has an IoU of at least 0.50 with the ground-truth bounding box. The YOLOv9 model achieved a mAP@50 of 0.9900, equivalent to 99.00%. This indicates that the model achieved highly accurate detection and localization of Scrabble rule violations at the 0.50 IoU threshold.

$$\text{mAP@50} = \frac{1}{N} \sum_{i=1}^N AP_i@50$$

4.5. Mean Average Precision at IoU 0.50–0.95 (mAP@50–95)

Unlike mAP@50, mAP@50–95 provides a more stringent evaluation because it considers detection performance across multiple IoU thresholds. A high value indicates that the model can both detect the correct rule violations and accurately localize them using bounding-boxes across multiple IoU thresholds. The YOLOv9 model achieved a mAP@50–95 of 0.9121, equivalent to 91.21%. This result demonstrates that the model maintained strong detection and localization performance even under stricter IoU requirements.

5. Discussion and Conclusion

This study developed a deep learning-based object detection framework for identifying and classifying predefined Scrabble rule violations from physical board images. YOLOv8, YOLOv9, and YOLOv10 were experimentally evaluated to determine the most suitable model for this task. Among the evaluated models, YOLOv9 achieved the strongest overall performance. These results demonstrate the model's ability to detect and accurately localize predefined rule violations on the Scrabble board. The use of bounding boxes provides visually interpretable feedback by indicating the locations of incorrect tile placements, thereby supporting post-game

assessment of rule adherence. The high detection performance across the evaluated metrics indicates that the proposed YOLO-based approach is suitable for automated identification and classification of the predefined rule-violation categories considered in this study.

Several limitations should be considered when interpreting these results. The generalizability of the model may be limited because the dataset was developed using a standard Scrabble board and a predefined range of gameplay conditions. Consequently, the model may not achieve the same level of performance when applied to boards with different visual designs, worn or damaged surfaces, different tile appearances, or substantially different board conditions. Variations in image acquisition conditions, including lighting intensity, shadows, reflections, glare, and camera angles, may also affect the visibility of tiles and board markings and, consequently, detection performance. Although data augmentation was applied during training, it may not fully represent all possible real-world environmental conditions. Furthermore, the model was trained using predefined rule-violation categories. Uncommon tile arrangements, complex combinations of violations, or violations not represented in the dataset may therefore not be detected with the same level of performance. The reported results should consequently be interpreted within the scope of the dataset, violation categories, and gameplay conditions evaluated in this study.

The findings demonstrate the potential of computer vision and deep learning for automated rule-adherence assessment in physical tabletop games. The proposed approach reduces reliance on manual inspection by identifying the locations and categories of predefined rule violations directly from board images. The visual feedback generated through bounding boxes can assist players in reviewing incorrect tile placements and understanding the locations of rule violations after gameplay. The results also indicate that a lightweight YOLO model such as YOLOv9 can provide effective detection performance for the structured visual environment of a physical Scrabble board. Thus, the proposed approach provides a practical basis for developing automated post-game rule-assessment tools for physical Scrabble gameplay.

In conclusion, this research developed and evaluated a YOLO-based approach for automated detection and classification of predefined Scrabble rule violations. The comparative evaluation showed that YOLOv9 achieved the strongest overall performance among the three evaluated models, demonstrating its suitability for the proposed rule-violation detection task. Future work should focus on expanding the dataset to include a wider range of board appearances, tile conditions, camera viewpoints, and environmental conditions, as well as incorporating additional and more complex Scrabble rule violations. The developed model could also be integrated into a real-time feedback mechanism to support immediate rule-adherence assessment during gameplay. Overall, the study provides a foundation for further development of computer vision-based systems for automated rule-violation detection and post-game analysis of physical Scrabble gameplay.

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