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ARTIFICIAL INTELLIGENCE THEORY AND APPLICATIONS

■ RESEARCH ARTICLE

Automated Recognition and Analysis of Biophilic Design Elements Using AI: An Interdisciplinary Approach in Architecture

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RECEIVED SEPTEMBER 19, 2025
ACCEPTED MARCH 2, 2026

CITATION Dikmen, Ç. B., Uzunhisarcıklı, E., Özbay Karakuş, M. & Kırmızı, E. (2026). Automated Recognition and Analysis of Biophilic Design Elements Using AI: An Interdisciplinary Approach in Architecture. *Artificial Intelligence Theory and Applications, 6* (1), 33-43.

Abstract

In today's architectural and urban design practices, the significance of biophilic design approaches is increasingly being recognized. Incorporating elements such as daylight, vegetation, water components, and organic materials has been shown to promote physical and psychological well-being. Despite their benefits, the assessment and implementation of these biophilic components are frequently carried out through manual inspection methods, which are labor-intensive, difficult to standardize, and prone to subjective interpretation. This research proposes an automated approach for identifying and spatially analyzing biophilic features by adapting and fine-tuning the YOLO (You Only Look Once) object detection algorithm for this specific application. Bridging the fields of architecture and artificial intelligence, the developed system provides a rapid, precise, and scalable means of evaluating biophilic design features in interior images within a computer vision–driven decision support workflow. Within the scope of this study, a dedicated visual dataset was compiled, with biophilic attributes systematically labeled and categorized, and transfer learning techniques were employed to retrain a YOLOv8-based model on this curated dataset. The trained model produces class-wise detections that are subsequently post-processed by a rule-based decision support layer to generate deficiency reports and actionable design recommendations (e.g., suggesting greenery or daylight-enhancing strategies when relevant elements are absent or underrepresented). The resulting system not only identifies missing or underrepresented biophilic components but also provides consistent feedback to support design refinement. To ensure practical usability, the model was integrated into a web-based platform, enabling users to upload images, visualize detections, and receive interpretable recommendations for improving biophilic strategies in their projects. Overall, the study's outcomes indicate that biophilic design features can be quantitatively assessed and automated through an integrated CV + DSS pipeline, supporting more scalable and repeatable evaluation in architectural and sustainable design contexts.

Keywords: Biophilic Design, YOLO Algorithm, Image Processing, Sustainable Architecture, Decision Support System

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Artificial Intelligence Theory and Applications, ISSN: 2757-9778. ISBN: 978-605-69730-2-4 © 2026 İzmir Bakırçay University

1. Introduction

With the rapid rise of modern urbanization, the intensified built environment of concrete-dominated cities has progressively weakened individuals' connection with nature, leading to adverse effects on both physical and psychological health [1]. As an increasing number of people spend prolonged hours in enclosed and artificial environments, issues such as elevated stress levels, attention deficits, fatigue, and even chronic illnesses have become more prevalent. Particularly during the COVID-19 pandemic, the impacts of interior spaces on individual well-being have become more visible, prompting growing interdisciplinary discussions on the need for environments that support interaction with nature [2, 3].

In response to these concerns, the concept of biophilic design has emerged as an effort to re-establish the human–nature connection within architectural practice. Rooted in Edward O. Wilson's notion of "biophilia," which describes an innate human affinity for the natural world, biophilic design proposes spatial strategies that facilitate closer and continuous interaction with nature [4]. This multidimensional approach advocates for the integration of natural light, vegetation, water features, natural materials, and nature-inspired forms and patterns into interior environments [5]. Far beyond an aesthetic choice, biophilic design represents an evidence-based methodology that enhances health, comfort, productivity, and user satisfaction [6].

A wide body of research has demonstrated that well-executed biophilic design can reduce stress, improve attention span, boost learning capacity, and enhance overall well-being [7–9]. Ulrich's pioneering study on the effects of nature views on patient recovery in healthcare settings is widely regarded as one of the earliest scientific findings in this field [10]. More recent experimental studies indicate that biophilic elements have a direct physiological impact on stress regulation and support emotional regulation [11, 12].

Biophilic strategies are relevant across many interior settings, including learning, healthcare, workplace, and residential environments. In particular, spaces used by children and young learners are often highlighted in the literature, because limited nature contact in educational settings and home environments may negatively affect cognitive, social, and emotional development. In today's world—characterized by digital screen exposure and artificial stimuli—children's bond with nature is diminishing, contributing to rising issues such as attention disorders, hyperactivity, and learning difficulties [13, 14]. At the same time, the practical challenge is not the recognition of biophilic value, but the difficulty of evaluating biophilic features consistently across projects and design iterations. These observations further motivate the systematic consideration of biophilic strategies in interior planning and architectural decision-making.

However, current methods for evaluating biophilic design mostly rely on manual observation, user feedback, and subjective assessment. This makes the process time-consuming and reliant on expert judgment, limiting consistency and measurability [15]. In particular, evaluating biophilic features from design visuals (e.g., interior photographs, renderings, or project images) is often performed through ad hoc review processes, making it difficult to compare alternatives, document decisions, or scale assessment across projects. In the literature, there is a notable lack of digital tools that enable objective identification and analysis of biophilic elements in interior spaces. Nevertheless, advancements in artificial intelligence and computer vision offer promising opportunities to address this gap [16].

Despite the growing adoption of biophilic principles, there is no widely used, repeatable pipeline that (i) automatically detects visually observable biophilic elements in interior images and (ii) converts these detections into interpretable feedback that can support design improvement.

The core problem addressed in this study is how to operationalize biophilic design assessment from interior images in a way that is repeatable, scalable, and interpretable. To avoid ambiguity in scope, the study is positioned strictly as a computer vision (CV) + decision support system (DSS) workflow. It does not present a human/participant-based evaluation; instead, it focuses on automated detection, quantitative summarization, and rule-based recommendation generation based on visual evidence.

This study proposes an innovative approach that integrates the disciplines of architecture and computer vision to enable objective, rapid, and automated identification of biophilic design elements in interior spaces. Utilizing a deep learning model based on the YOLO (You Only Look Once) algorithm, the system aims to automatically detect and analyze visual data containing biophilic features such as natural light cues, plants, water-related elements, and nature representations. The model, trained on a custom-built dataset, produces class-wise detections and derives simple spatial summaries (e.g., presence/absence and distribution patterns), which are then used to trigger design suggestions based on identified deficiencies.

The decision support system developed within this study is designed to guide designers and architects, and may also be useful for other stakeholders (e.g., educators, healthcare professionals, and planners) who review interior environments, involved in interior planning by providing consistent, evidence-linked feedback. Supported by a web-based user interface, the system enables users to upload images of their spaces, view detection outputs, and receive recommendation messages for improvement. By providing an objective, consistent, and scalable method for evaluating biophilic design from images, this study aims to contribute to the development of healthier, more sustainable, and user-friendly interior environments. In summary, the main contributions are: (1) the creation and annotation of a visual dataset of interior scenes with biophilic categories, (2) fine-tuning a YOLO-based object detection model to identify these categories, and (3) integrating detection outputs into a rule-based DSS and web interface that produces deficiency reporting and actionable recommendations. The development process and workflow of the architectural decision support system, along with dataset creation and subsequent steps, are illustrated in Figure 1.

2. Materials and Method

2.1. Creation and Annotation of the Visual Dataset

An extensive and original visual dataset was developed, comprising interior scenes that include visually observable biophilic cues such as plants/vegetation, animal figures or representations, water-related cues, landscape visuals (e.g., window views), natural light cues, natural materials (e.g., wood, stone), and nature-inspired patterns. Images were annotated using bounding boxes according to a predefined labeling guideline aligned with biophilic design principles. To support generalization under varying indoor conditions (illumination, occlusion, and clutter), data augmentation techniques—including rotation, zooming, and horizontal/vertical flipping—were applied.

For clarity and consistency in the detection task, the dataset was organized into the following categories:

- Natural light or natural materials (e.g., wood, stone)
- Plants and green walls
- Background
- Landscape visuals (e.g., window views)
- Animal figures and representations

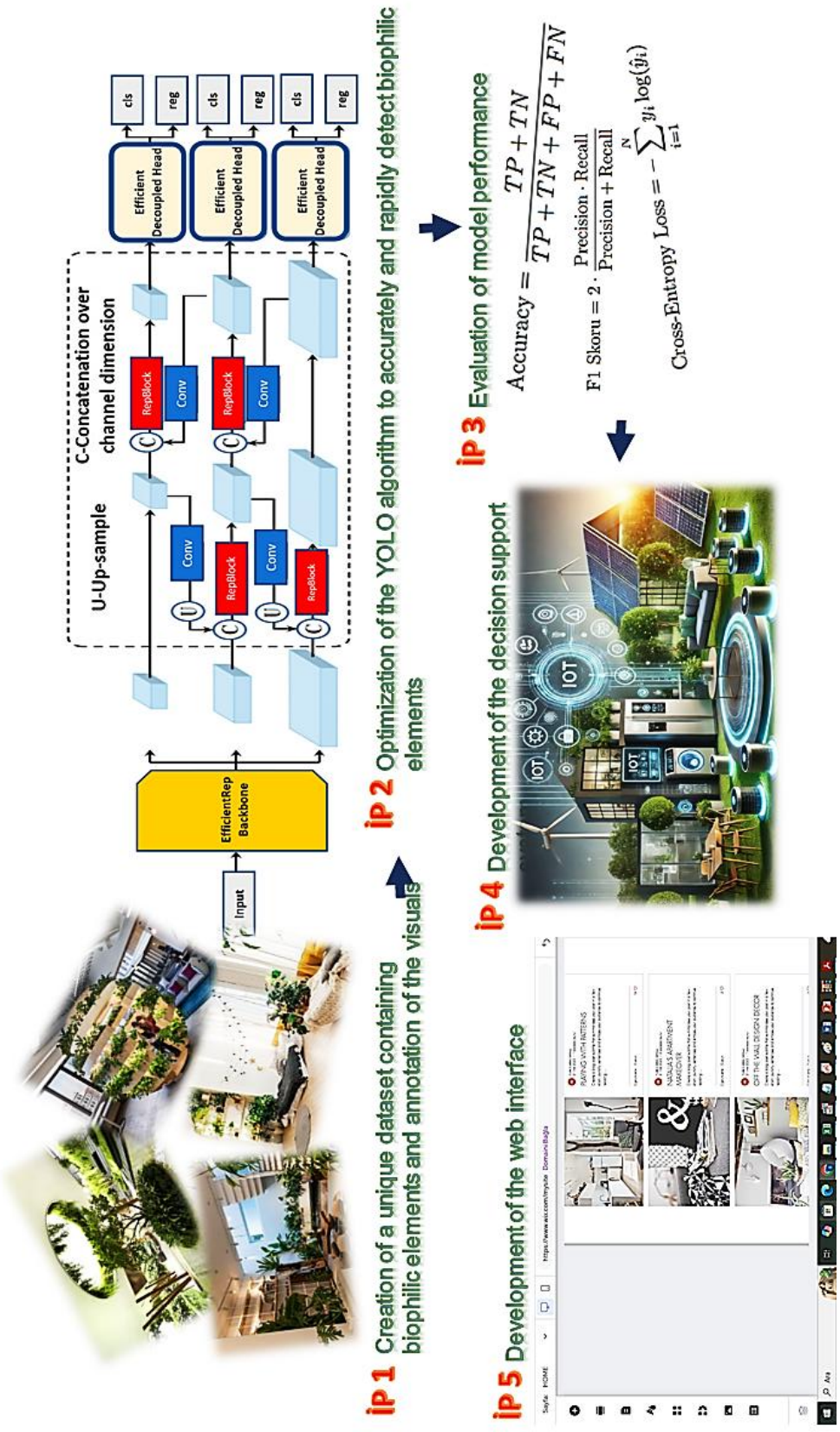


Figure 1. Workflow diagram

The collected images were annotated accordingly and diversified using the augmentation procedures above. The dataset was then prepared for model training by standard preprocessing steps required by the YOLO pipeline (e.g., resizing and format conversion). In this study, the “background” category is included as a dataset label; however, it is treated carefully during evaluation and interpretation because background-like regions may absorb ambiguous detections.

2.2. Training and Customization of the YOLO Algorithm

After dataset preparation, a YOLO-based object detection model was developed to detect biophilic elements rapidly and accurately. The YOLOv8 version was used as the base model, and transfer learning was applied using pre-trained weights to accelerate convergence and improve performance with limited domain-specific data. The model was retrained on the biophilic dataset.

During training, key hyperparameters (e.g., batch size, number of epochs, learning rate) were tuned through experimentation to optimize detection performance across classes. Standard augmentation was applied during training to improve robustness. The training objective was to achieve stable class-wise detections for each biophilic category, suitable for downstream decision support.

To improve reproducibility, the following implementation details are reported in the revised manuscript: model version (YOLOv8), training configuration (batch size, epochs, learning rate), and the augmentation strategy used. Hardware/software details and exact values can be provided in the final version where applicable.

2.3. Evaluation Protocol

To ensure consistency and transparency in performance evaluation, standard object detection evaluation practices were adopted. A predicted bounding box is considered a true positive when it matches a ground-truth annotation of the same class with an Intersection-over-Union (IoU) value of at least 0.50. Predictions below this threshold are treated as false positives, while unmatched ground-truth boxes are counted as false negatives. Non-maximum suppression (NMS) is applied to remove duplicate detections, and a fixed confidence threshold is used to filter low-confidence predictions. Based on this matching procedure, class-wise precision, recall, and F1-score are computed, along with mean Average Precision at IoU = 0.50 (mAP@0.50), following common evaluation conventions in object detection.

2.4. Development of the Decision Support System

The outputs of the object detection model were integrated into a decision support system (DSS) designed to identify potential deficiencies in biophilic design from interior images. The DSS produces two main outputs: (i) a Deficiency Report and (ii) a Recommendation Module. The Deficiency Report flags missing or underrepresented biophilic elements based on detection results, and the Recommendation Module provides actionable suggestions linked to the detected evidence.

The deficiency identification logic follows a rule-based approach. After the YOLO model processes an image, detected classes are compared against predefined minimum criteria for each category (e.g., plants/greenery, natural light cues, or water-related cues). If certain elements are not detected or appear below the defined threshold, the system

flags them as deficiencies. This rule-based assessment enables a consistent and quantifiable evaluation process.

Once deficiencies are identified, the DSS generates automated recommendations using a predefined rule set. For example, if no plant-related elements are detected, the system suggests: “No greenery detected—consider adding potted plants or a green wall.” If natural light cues are underrepresented, the system may recommend: “Low natural light—consider increasing glazing area or using transparent materials.” These tailored suggestions support design refinement by translating detection outputs into interpretable guidance.

2.5. Development of the Web-Based Interface, Spatial Analysis and Visualization

To ensure accessibility, an interactive web platform was implemented using Flask. The interface allows users to upload interior images and conduct biophilic analysis through the integrated CV + DSS pipeline. The platform includes:

- Image Upload Module: Upload interior images.
- Analysis Panel: Display detected biophilic elements with bounding boxes and summarize detected classes.
- Recommendation System: Show deficiency flags and recommendation messages generated by the DSS.
- Educational Module: Provide example projects and informational content to raise awareness of biophilic strategies.

The spatial distribution of detected elements is supported through visual overlays and heatmap-style visualizations to help users interpret where biophilic cues are concentrated or missing, enabling more informed design decisions.

3. Performance Evaluation Of The AI-Based Biophilic Decision Support System

This section evaluates the performance of the proposed AI-based biophilic decision support system using quantitative object detection metrics and system-generated outputs. The evaluation focuses on the detection capability of the YOLO-based model across biophilic categories and on how these detection results are utilized by the rule-based decision support layer. No human- or participant-based evaluation is conducted; all results are derived directly from model predictions and predefined decision rules.

3.1. Visual Detection Performance

Figure 2 illustrates representative examples of object detection results produced by the trained YOLO model. The model successfully identifies multiple biophilic categories, including plants, natural materials (e.g., wood), natural light cues, and nature-inspired patterns. Each detected element is labeled with its corresponding class and enclosed by a bounding box.

These visual outputs demonstrate the model’s ability to localize and classify biophilic elements within interior scenes, forming the basis for subsequent quantitative analysis and rule-based assessment. The bounding-box detections enable numerical summarization of detected elements, such as presence/absence and approximate spatial distribution.

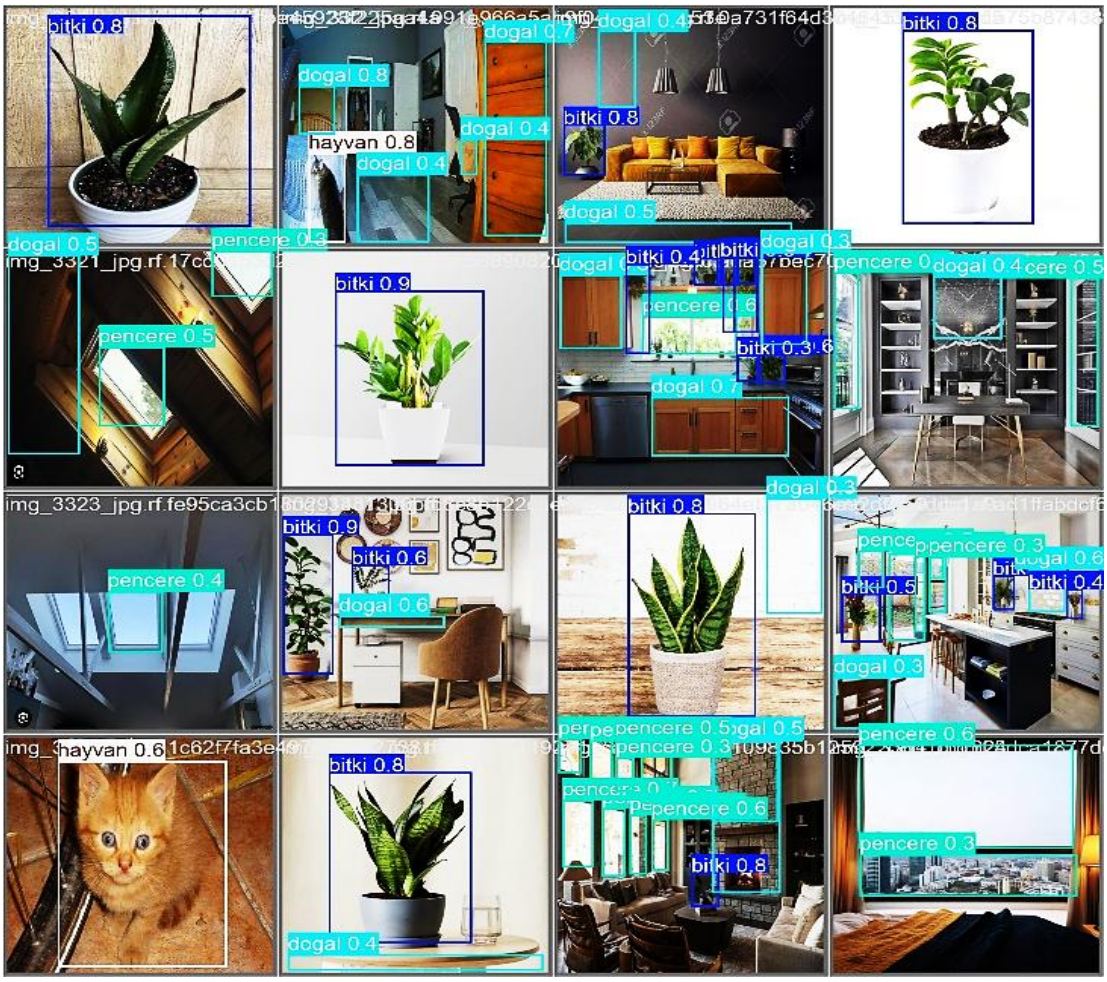


Figure 2. Object detection results for selected biophilic categories.

3.2. Quantitative Performance Evaluation

Quantitative performance is summarized using a confusion matrix (Figure 3), which reflects the agreement between predicted class labels and ground-truth annotations derived from object detection matching. Rows represent predicted classes, while columns correspond to true classes after applying the defined matching protocol.

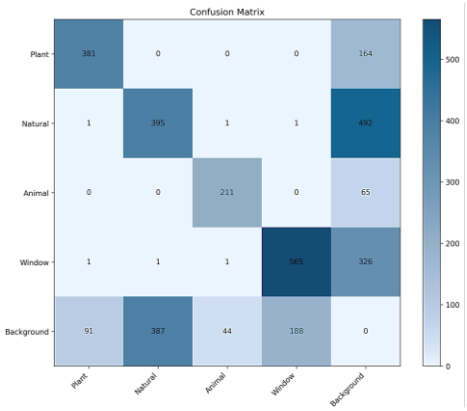


Figure 3. Confusion Matrix

Based on this matrix, class-wise precision, recall, and F1-score values are computed and reported in Table 1.

Table 1. Quantitative Evaluation Results For Yolo-Based Biophilic Element Detection

Class	Precision	Recall	F1 Score
Bitki (Plant)	**0.804**	**0.699**	**0.748**
Doğal (Natural Materials)	0.504	0.444	0.472
Hayvan (Animal)	**0.821**	**0.764**	**0.792**
Pencere (Window)	0.749	0.632	0.686
Arkaplan (Background)	**0.013**	**0.021**	**0.047**

Class-wise analysis shows that visually distinctive categories such as plants and windows achieve relatively strong performance, while categories with higher visual variability or contextual ambiguity—such as natural materials—exhibit lower recall and F1-scores. A substantial portion of misclassifications corresponds to instances predicted as background, indicating that the model tends to over-assign the background class when uncertainty is high. This behavior contributes to reduced overall accuracy and highlights the impact of class imbalance and overlapping visual features.

Figure 4 presents training and validation curves for key metrics, including bounding box localization loss (box_loss), classification loss (cls_loss), and distribution focal loss (dfl_loss). During training, these losses consistently decrease, indicating improved localization and classification performance. Precision and recall metrics increase over epochs, suggesting more reliable detection with fewer false positives.

On the validation side, box_loss decreases initially and then slightly increases toward later epochs, which may indicate mild overfitting. While validation classification-related losses generally decline, their late-stage increase suggests that additional regularization strategies (e.g., early stopping or expanded augmentation) could further improve generalization. The model achieves a mean Average Precision of approximately 75% at IoU = 0.50 (mAP@0.50) and around 35% across stricter IoU thresholds (mAP@0.50–0.95), indicating consistent detection performance under varying overlap criteria.

Beyond detection metrics, the system produces rule-based decision support outputs derived directly from detection results. Based on the presence or absence of specific biophilic categories, the DSS generates automated recommendation messages, such as:

“No green elements detected. Consider integrating potted plants or a green wall.”

“Low natural light detected. Consider increasing glazing or using transparent materials.”

“No water-related cues detected. Consider adding a small indoor water element or equivalent sensory cue.”

These outputs do not rely on user feedback or participant evaluation; instead, they translate quantitative detection results into interpretable guidance. This capability enhances the practical relevance of the system by linking object detection outputs to design-oriented recommendations in a transparent and repeatable manner.

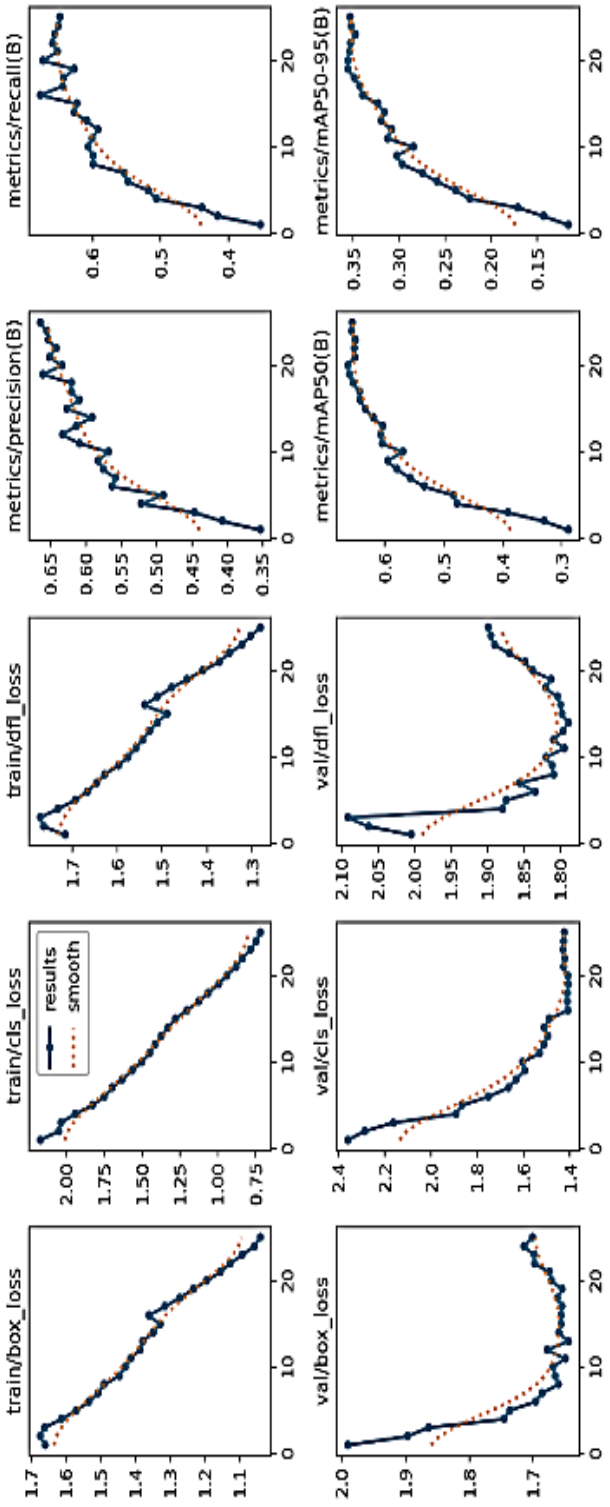


Figure 4. Metrics obtained during the training process of the YOLO-based object detection model.

4. Results and Discussion

This section reports the outcomes of the proposed AI-based biophilic decision support workflow in terms of object detection performance, error patterns, and system-level DSS

outputs derived from detection results. The reported findings are limited to the computer vision model and the rule-based recommendation layer; the manuscript does not include a human/participant-based evaluation.

The quantitative evaluation presented in Section 3 indicates that the YOLO-based detector can identify multiple biophilic categories in interior images with varying levels of accuracy across classes. Classes that are visually distinctive (e.g., plants and window/landscape-related cues) achieve stronger performance, whereas categories with higher visual variability and contextual dependence (e.g., natural materials) remain more challenging. A recurring error pattern is the tendency to assign ambiguous regions to the background class, which is consistent with the observed low precision/recall for background and the misclassification counts reported in the confusion matrix. This behavior likely reflects class imbalance and overlap between textures (e.g., wood/stone surfaces versus surrounding interior elements), suggesting that refined labeling guidelines, additional training samples, and targeted augmentations could improve class separability.

In addition to detection metrics, the DSS layer translates class-wise detections into interpretable deficiency flags and recommendation messages using predefined rules. For example, absence or underrepresentation of greenery triggers suggestions for plant integration; low natural light cues trigger daylight-enhancing strategies; and missing water-related cues trigger water-element or equivalent sensory-cue suggestions. Importantly, these DSS outputs are directly linked to detection evidence, which improves transparency and supports repeatable decision-making across design iterations.

From an interdisciplinary perspective, the contribution of this study lies in operationalizing biophilic assessment as a repeatable CV + DSS pipeline that connects model outputs to design-oriented feedback. The curated and annotated dataset introduces a structured biophilic taxonomy for interior images, and the adaptation of a YOLO-based detector demonstrates feasibility for automated identification in architectural contexts. The integration into a prototype web-based DSS further supports practical use by enabling users to upload images, visualize detections, and receive evidence-linked recommendations. These outcomes provide a foundation for future work focused on improving model robustness, expanding the dataset and biophilic categories, and refining the rule base for more context-sensitive guidance.

5. Conclusion

This study presented an AI-assisted approach for assessing biophilic design features in interior images by integrating a YOLO-based object detection model with a rule-based decision support system and a web-based interface. The proposed workflow enables automated identification, quantitative summarization, and interpretable recommendation generation for biophilic cues, offering a more scalable and repeatable alternative to purely manual review.

The main outcomes achieved in this work are: (i) the creation and annotation of a domain-specific dataset of biophilic categories in interior scenes, (ii) fine-tuning a YOLO-based detector to recognize these categories, and (iii) deploying the model within a DSS that produces deficiency reporting and actionable recommendations through transparent rules. These contributions advance the integration of computer vision methods into architectural design evaluation by linking detection outputs to practical design guidance.

Future work will focus on improving detection performance for visually heterogeneous classes (e.g., natural materials) by expanding and balancing the dataset, refining labeling guidelines, and applying additional training strategies (e.g., targeted augmentations and early stopping). We also plan to expand the DSS rule base to support richer biophilic taxonomies and multi-image/project-level reporting, enabling more comprehensive assessment in iterative architectural workflows.

Declarations

Funding

This research received no external funding.

Data Availability

The data presented in this study are available on request from the corresponding author.

Conflicts of interest

The authors declare no conflict of interest.

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