Information Technology in Economics and Business
Cutting-Edge Scientific Solutions

e-ISSN: 3023-8943
RESEARCH ARTICLE
Vol.2 / No.1 / 2025 / pp.24-31
https://doi.org/10.69882/adba.iteb.2025014

Location-Based Technology for Real-Time Artifact Recognition in Businesses

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ABSTRACT The recognition of historical artifacts play a crucial role in sustaining cultural heritage and advancing tourism. Despite advancements in object detection technologies, accurately identifying artifacts in diverse geographical and environmental contexts remains a significant challenge. Existing models often struggle to adapt to region-specific features and the complexity of historical artifacts, limiting their practical applications. To address these limitations, this study evaluates the potential of YOLOv4, YOLOv7-X, and YOLOv9c models for historical artifact recognition, with a particular focus on location-based segmentation. Geographically distinct datasets were utilized for training and evaluation, enabling the models to achieve higher accuracy in region-specific artifact detection. Among the tested models, YOLOv9c demonstrated superior performance, achieving the highest metrics across accuracy (96%), precision (93%), recall (95%), and mean average precision (mAP, 71%), making it the best-performing model. These results highlight YOLOv9c's robustness and adaptability to complex datasets and diverse artifact characteristics. A user-friendly application interface was also developed, allowing real-time detection and providing detailed historical information about the artifacts. However, challenges such as the high computational cost of training YOLOv9c on high-resolution datasets were observed, particularly when compared to YOLOv4, which was computationally efficient but less accurate. YOLOv7-X offered a balance between performance and computational efficiency. The results demonstrate that location-based segmentation significantly enhances detection accuracy, making this approach highly effective for real-world applications in cultural heritage preservation and tourism.

KEYWORDS
Tourism technologies
Artificial intelligence
object detection
Artifact recognition
YOLO
Businesses

INTRODUCTION

Artificial intelligence (AI) plays a pivotal role in the digital transformation of the tourism sector by offering personalized experiences tailored to tourists' individual needs. AI-based mobile applications facilitate tourists' travel planning processes and optimize their itineraries. For instance, augmented reality and natural language processing integration in guiding services enriches the user experience by providing real-time information (Devlin *et al.* 2018; Zouni and Kouremenos 2008). Furthermore, object recognition algorithms serve as an important tool for promoting historical artifacts and cultural assets (Wang *et al.* 2025). In addition to mobile devices, compact computers with higher performance capabilities can also be utilized to handle computationally intensive AI tasks effectively, as demonstrated in studies on the effectiveness of machine learning models for various predictive tasks (Coşar and Kiran 2018; Deniz 2024). Blockchain technology has also been proposed to enhance data security and integrity in tourism-related autonomous systems, providing resilient solutions for location-based tasks, as shown in UAV applications (Cosar and Kiran 2021).

Manuscript received: 14 January 2025,
Revised: 28 January 2025,
Accepted: 29 January 2025.

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AI also offers activity recommendations based on tourists' interests, which are continuously improved through user feedback (Molina-Collado *et al.* 2022; Loureiro *et al.* 2020). Specifically, genetic algorithms and machine learning methods in route planning optimize travel times and enhance visitor satisfaction (Homay *et al.* 2019). The use of AI in customer service has also become widespread, with intelligent chatbots answering frequently asked questions and making travel experiences more accessible for tourists (Kılıçhan and Yılmaz 2020).

Academic studies on the integration of AI in the tourism sector provide an in-depth analysis of the digital transformation in this industry. Seyfi et al. (Seyfi *et al.* 2025) analyzed the adoption processes of generative artificial intelligence technologies in the tourism sector, focusing on personal factors that influence tourists' travel planning decisions. Guan et al. (Guan *et al.* 2025) examined human-robot interactions and assessed the impact of AI-based robotic services on customer satisfaction. Rather (Rather 2025) investigated consumers' perceptions of AI-based technologies in terms of self-congruity and perceived value. Khairy et al. (Khairy *et al.* 2025) explored the effects of AI-supported leadership approaches aimed at enhancing green competitiveness and human capital. Moreover, Liu et al. (Liu *et al.* 2025) provided a framework for the application of machine learning techniques in sentiment analysis within tourism research.

In recent years, object recognition technologies have made significant progress, particularly with innovations in the YOLO (You Only Look Once) series of models. YOLOv7 (Wang *et al.* 2022) provides optimization in terms of speed and accuracy, effectively operating on mobile devices with low power consumption requirements. This model has become a standard for real-time applications and complex scene detection. A more advanced version, YOLOv9 (Wang *et al.* 2025), improves performance on large-scale datasets and has been adopted in various industries, including tourism, due to its enhanced features. Conversely, region-based algorithms such as Faster R-CNN (Ren *et al.* 2016) are preferred for projects requiring high precision, delivering effective results in detecting objects in tourist locations. In the study by Hilali et al. (Hilali *et al.* 2023), Faster R-CNN and YOLOv7 models were compared, revealing that Faster R-CNN excels in detailed scenes, while YOLOv7 offers advantages in speed.

Object recognition technologies play a vital role in promoting cultural heritage and natural sites in the tourism industry. Guidosse et al. (Guidosse *et al.* 2025) investigated the combined use of camera traps and AI technologies to monitor visitor activity in the Ardenne region of Belgium. Sánchez-Juárez et al. (Sánchez-Juárez and Paredes-Xochihua 2024) proposed a solution integrating object recognition algorithms into augmented reality (AR) projects to enhance tourists' interactive experiences. Shi et al. (Shi *et al.* 2024) developed the YOLOX network model to dynamically recognize tourist destinations in mountainous regions with complex scenes. Velvizhy and Sherly (Sherly and Velvizhy 2024) focused on AI-supported identification and speech transformation systems for religious figures, offering a new approach to preserving cultural heritage. Tsurcanu and Alexandrescu (Agapie *et al.* 2024) proposed a system using cloud-based object recognition solutions to optimize tourists' destination searches. Lu et al. (Lu *et al.* 2025) developed an autonomous campus tour guide vehicle, combining object recognition with LiDAR positioning to enhance the tourist experience.

In this study, the performance of object recognition algorithms was analyzed using selected artifacts from the İzmir region. The training dataset consisted of images from cultural heritage sites such as the House of the Virgin Mary, Ephesus Ancient City, and the Library of Celsus. Each artifact was captured from various angles, resulting in a total of 762 images, which were trained using YOLOv4, YOLOv7, and YOLOv9 models. The training process adopted a location-based approach, optimizing each artifact group on separate models. A four-fold cross-validation method was employed to evaluate the models' performance in terms of accuracy, precision, and recall.

The main contributions of this study are as follows:

- A location-based object recognition approach incorporating YOLOv4, YOLOv7, and YOLOv9 models has been proposed for the recognition of selected historical artifacts in İzmir.
- Comprehensive cross-validation methods have been applied to optimize the artifact recognition processes, and accuracy, precision, and recall metrics have been analyzed in detail for each model.
- The location-based training approach employed in this study enhanced regional recognition performance by modeling datasets obtained from different cultural regions.
- The high accuracy rates and real-time recognition capabilities of the YOLOv9 model have been demonstrated as a potential tool for the preservation and promotion of cultural heritage sites.

The rest of this paper is organized as follows: In the Proposed Methodology section, object recognition algorithms, location-based training strategy, cross-validation methods, and performance evaluation metrics will be explained. Next, the Data Collection and Preprocessing section will present the creation, labeling, and preparation of the dataset for model training. In the Experiments and Results section, the performances of YOLOv4, YOLOv7, and YOLOv9 models will be compared using various metrics, and the obtained findings will be analyzed in detail. The Discussion section will address the advantages and disadvantages of the location-based object recognition approach, as well as identify the limitations of the study and future research directions. Finally, the Conclusion section will summarize the main findings of the study and provide an overall assessment of the paper.

PROPOSED METHODOLOGY

This section summarizes the methodology employed in this study to achieve the research objectives. It provides a comprehensive explanation of the object recognition algorithms used, with a particular focus on the YOLO family and its variants. Additionally, the rationale behind adopting a location-based training strategy is explained, highlighting its potential to enhance the accuracy of object recognition in specific environments. Furthermore, the cross-validation techniques applied to ensure the robustness and generalizability of the models are discussed. Finally, this section details the performance evaluation metrics used to assess the effectiveness of the trained models.

Object Detection Algorithms

In this study, YOLOv4, YOLOv7-X, and YOLOv9c models were utilized for the recognition of historical artifacts. These models are advanced variants of the YOLO (You Only Look Once) family, optimized to meet real-time and high-accuracy requirements in object detection. Their architectural designs incorporate innovative techniques to maximize speed, accuracy, and computational efficiency.

YOLOv4 (Bochkovskiy *et al.* 2020) achieves an effective balance between accuracy and speed through its optimized architecture. It incorporates innovations such as the CSPDarknet53 backbone, Mish activation function, Self-Adversarial Training (SAT), and Cross Mini-Batch Normalization (CmBN). Additionally, the inclusion of the Spatial Pyramid Pooling (SPP) module enhances the model's ability to detect historical artifacts at various scales and in complex backgrounds.

YOLOv7 (Wang *et al.* 2022) is an extended variant designed to enhance the recognition performance of historical artifacts by utilizing the Efficient Layer Aggregation Network (E-ELAN) framework. This model applies expansion and reorganization techniques to optimize parameter usage and improve learning capacity. Moreover, its dynamic label assignment strategies refine training accuracy across multi-layer output heads. In this study, the YOLOv7-X variant was used.

YOLOv9 (Wang *et al.* 2025) represents the latest advancements in historical artifact recognition. It combines the General Efficient Layer Aggregation Network (GELAN) architecture with Programmable Gradient Information (PGI) mechanisms, effectively preventing information bottlenecks and ensuring the seamless propagation of features throughout the network. This model excels in the detailed and accurate classification and localization of historical artifacts. The YOLOv9c variant was employed in this study.

These models were selected due to their diverse strengths in artifact detection: YOLOv4 stands out for its speed and foundational innovations, YOLOv7-X excels with its extended architecture and flexibility, and YOLOv9c delivers superior performance with advanced gradient management and feature preservation mechanisms. The comparative performance metrics of the models are summarized in Table 1.

Location-Based Training Strategy

The location-based training strategy employed in this study aims to enhance the performance of object recognition algorithms in identifying historical artifacts by leveraging geographically specific datasets. This approach is designed to improve detection accuracy by training the models with data collected from various cultural and historical sites. Figure 1 illustrates the geographical distribution of the key regions used in the dataset, which include the House of the Virgin Mary, Ephesus Ancient City, and the Library of Celsus.

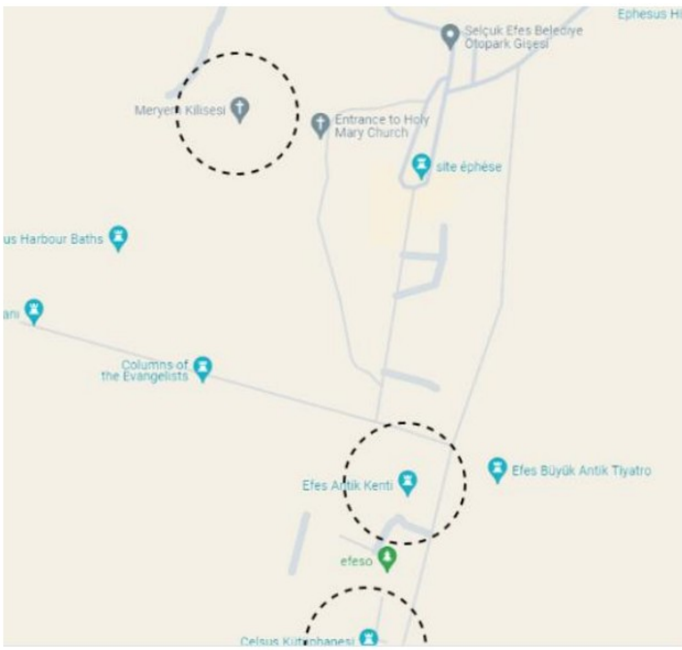

Figure 1 Geographical distribution of training locations: House of the Virgin Mary, Ephesus Ancient City, and Celsus Library.

For this purpose, artifact images were collected from each region, and the dataset was diversified to include various perspectives, lighting conditions, and environmental factors specific to each location. This localized data collection approach enables the model to learn distinctive features and contextual elements unique to each artifact. For instance, the House of the Virgin Mary, located in a wooded area, required the model to distinguish historical elements from the natural surroundings, while the Ephesus Ancient City, characterized by extensive ruins, presented challenges in separating structures from large-scale backgrounds.

The training process involved dividing the data into subsets corresponding to each region and applying model optimizations based on location-specific details within these subsets. This process was supported by data augmentation techniques, such as random rotation, brightness adjustments, and cropping, to simulate real-world variability. Additionally, cross-validation was performed on these subsets, ensuring the model's generalizability across all target regions while maintaining region-specific performance capabilities.

The location-based training strategy significantly improved detection accuracy, particularly in regions with visually complex or overlapping features. This result underscores the effectiveness of geographically tailored datasets in enhancing the capabilities of advanced object recognition algorithms.

Cross-Validation and Performance Evaluation

In this study, a 4-fold cross-validation method was employed to evaluate the performance of the YOLOv4, YOLOv7-X, and YOLOv9c models in historical artifact recognition tasks. The cross-validation approach enabled the assessment of the models' overall accuracy and generalizability by using each regional subset of the dataset alternately for both training and testing purposes.

The dataset was divided into four equal parts, with each part serving as the test set once, while the remaining three parts were used for training. During the cross-validation process, the following performance metrics were calculated for each model:

- **Accuracy**: The ratio of all correct predictions to the total number of predictions, expressed as:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{1}$$

  where:

  - TP: True Positives,
  - TN: True Negatives,
  - FP: False Positives,
  - FN: False Negatives.

- **Precision**: Measures how many of the predicted positive cases are actually correct, calculated as:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{2}$$

- **Recall**: Measures how many of the actual positive cases are correctly predicted, expressed as:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{3}$$

- **mAP (Mean Average Precision)**: Represents the mean of the Average Precision (AP) values across all object classes, calculated as:

$$\text{mAP} = \frac{1}{N} \sum_{i=1}^{N} \text{AP}_i \tag{4}$$

  where:

  - N: Total number of object classes,
  - AP_i: Average Precision for the i-th object class.

DATA COLLECTION AND PREPROCESSING

The data collection and preprocessing process used in this study was meticulously designed to ensure the robust and effective development of historical artifact recognition models. Images of cultural and historical artifacts were collected from three significant locations: **House of the Virgin Mary**, **Ephesus Ancient City**, and **Celsus Library**. These locations were selected for their architectural diversity and varying environmental conditions, providing a rich dataset for model training and evaluation.

Table 1 **Comparative performance of YOLO models used for historical artifact recognition.**

Model	Backbone	AP (%)	Key Advantages	Limitations
YOLOv4	CSPDarknet53	43.5	Robust feature extraction, scalable architecture	Limited suitability for lightweight applications
YOLOv7-X	E-ELAN	52.9	Improved efficiency, dynamic label assignment	More complex training process
YOLOv9c	GELAN and PGI	57.8	Superior gradient management, state-of-the-art accuracy	Higher computational requirements

Data Collection

At each location, photographs were captured under various lighting conditions and from different perspectives to enhance the diversity and generalizability of the dataset. A total of 762 images were collected, and the distribution of these images across the locations is presented in Table 2. These images captured fine details such as artifact textures, shapes, and environmental contexts, enabling the models to distinguish artifacts from their surroundings.

Table 2 Distribution of collected images across landmarks.

Landmark	Number of Images	Percentage (%)
House of the Virgin Mary	250	33
Ephesus Ancient City	320	42
Celsus Library	192	25
Total	762	100

Preprocessing Techniques

The collected images were subjected to various preprocessing steps to standardize and augment the dataset. Table 3 summarizes the key preprocessing techniques applied.

Table 3 Preprocessing techniques applied to the dataset.

Step	Description
Resizing	All images were resized to 640×640 pixels to match the input size requirements of YOLO models.
Data Augmentation	Random rotations, brightness and contrast adjustments, horizontal flips, and zooming were applied to simulate real-world scenarios and prevent overfitting.
CLAHE Enhancement	Contrast Limited Adaptive Histogram Equalization (CLAHE) was applied to enhance contrast in low-light or high-glare images, improving feature visibility.
Annotation	Artifacts in the images were manually labeled with bounding boxes following the YOLO format, compatible with YOLO training pipelines.

Dataset Splitting

The processed dataset was divided into three subsets for training, validation, and testing based on the locations. Initially, 15% of the total data from each location was allocated to the testing subset. From the remaining data, 25% was assigned to the validation subset, and the remaining 75% was used for training. This approach ensures that the models are trained and evaluated on geographically diverse subsets while maintaining proportional representation of each location in all phases of the process. Table 4 provides the detailed breakdown of the dataset split for each location. These data have also been augmented using data augmentation methods to increase fourfold.

Table 4 Location-based dataset splitting with test counts and adjusted validation/training.

Location	Subset	Images	Note
House of the Virgin Mary	Testing	38	Test set only
	Validation	53	25% of remaining
	Training	159	75% of remaining
Ephesus Ancient City	Testing	48	Test set only
	Validation	68	25% of remaining
	Training	204	75% of remaining
Celsus Library	Testing	29	Test set only
	Validation	41	25% of remaining
	Training	122	75% of remaining
Total		762	

EXPERIMENTS AND RESULTS

This section presents the experimental framework and results obtained during the evaluation of the YOLOv4, YOLOv7-X, and YOLOv9c models for historical artifact recognition. The experimental setup, including the hardware, software, and training parameters, is described in detail. The dataset preparation, which forms the basis of these experiments, is discussed in Section 'Experiments and Results'. The performance of each model is evaluated on the test dataset using metrics such as accuracy, precision, recall, and mAP. Additionally, the results are visualized through tables, charts, and example outputs, highlighting the models' strengths and limitations in real-world scenarios.

Experimental Setup

This section provides details on the hardware and software infrastructure used, the training parameters for each model, and a brief summary of the dataset utilized in this study.

Hardware and Software Infrastructure The experiments were conducted on a system equipped with an Intel Core i9-10920X CPU running at 3.50 GHz with 24 threads, 64 GiB of RAM, and two NVIDIA RTX A5000 GPUs, each with 24 GiB of VRAM. The system was running Ubuntu 20.04.6 LTS (64-bit) with NVIDIA Driver Version 535.216.01 and CUDA Version 12.2. For YOLOv4, the TensorFlow framework was used, while YOLOv7-X and YOLOv9c were implemented using the PyTorch framework.

Training Parameters Each model was trained using specific parameters tailored to its architecture and requirements:

- **YOLOv4:** The input image size was set to 416×416, with a batch size of 32. The model training utilized an initial learning rate of 0.001, following a step decay schedule for gradual reduction during training.
- **YOLOv7-X:** The input image size was 640×640, with a batch size of 32. The model was trained for 50 epochs, using the default learning rate settings.
- **YOLOv9c:** The input image size was 640×640, with a batch size of 32. The model was trained for 50 epochs, using the default learning rate settings.

Experimental Results

The performance of the YOLOv4, YOLOv7-X, and YOLOv9c models was evaluated on the test dataset using four key metrics: accuracy, precision, recall, and mean average precision (mAP). These metrics provided a comprehensive assessment of the models' ability to accurately detect and classify historical artifacts. The results are summarized in Tables 5, 6, 7, and 8, respectively.

The accuracy results, detailed in Table 5, highlight the differences in model performance. YOLOv4 achieved an average accuracy of 84% across the entire dataset, with location-based accuracies of 86%, 92%, and 94% for Celsus Library, House of the Virgin Mary, and Ephesus Ancient City, respectively, resulting in a location-based average of 91%. YOLOv7-X demonstrated an improvement with an overall accuracy of 85% and a location-based average of 95% (93%, 95%, 96%). Meanwhile, YOLOv9c outperformed both models, achieving an overall accuracy of 85% and a location-based accuracy of 96% (93%, 95%, 98%).

Precision, presented in Table 6, further distinguishes the models' performances. YOLOv4 achieved an overall precision of 81%, with location-based precision values of 87%, 88%, and 91% for the three locations. YOLOv7-X improved on these metrics with an overall precision of 83% and a location-based precision of 93% (91.0%, 93%, 97%). YOLOv9c, delivering the highest precision, achieved 84% overall and 93% location-based precision (92%, 94%, 94%).

The recall results, shown in Table 7, reveal similar trends. YOLOv4 achieved an overall recall of 84%, with location-based recall values of 90%, 86%, and 94%. YOLOv7-X improved these scores with an overall recall of 86% and location-based recall values of 94% (91%, 95%, 96%). YOLOv9c, once again, delivered the highest recall, achieving 86% overall and 95% location-based recall (92%, 95%, 97%).

Finally, mAP results are summarized in Table 8. YOLOv4 achieved an overall mAP of 66% and a location-based mAP of 68% (65%, 68%, 70%). YOLOv7-X improved these results with an overall mAP of 68% and a location-based mAP of 69% (68%, 69%, 71%). YOLOv9c, demonstrating the best performance, achieved an overall mAP of 70% and a location-based mAP of 71% (69%, 71%, 72%).

The results of the 4-fold cross-validation for the YOLOv9c model are presented in Table 9. Among the folds, Fold 3 achieved the best performance, with a recall of 95% and a precision of 93%. These values indicate the model's capability to accurately identify true positives and maintain high precision. Additionally, Fold 3 achieved accuracy and mAP values of 96% and 71%, respectively, demonstrating well-balanced overall performance. Based on these results, the model trained on Fold 3 was selected as the final model due to its superior metrics, which are critical for historical artifact recognition tasks.

To illustrate the real-world application of the developed system, Figure 2 demonstrates the interface of the artifact recognition application. The application first captures the artifact's image and determines its location. The corresponding YOLOv9c model is then applied based on the location, enabling the detection of the artifact. Once detected, the application provides detailed information about the artifact, including its historical significance and architectural details. In this example, the image of the Library of Celsus is processed, showcasing the system's capability to integrate artifact detection with user-friendly informational feedback.

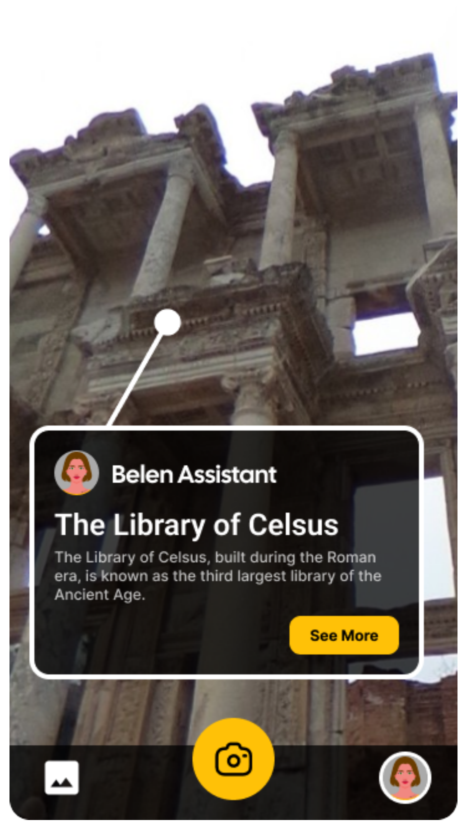

Figure 2 The interface of the artifact recognition application showing the Library of Celsus as an example output.

Table 5 Accuracy (%) results for each model across all datasets.

Model	Average	Celsus Library	House of Virgin Mary	Ephesus Ancient City
YOLOv4 (Overall)	84	-	-	-
YOLOv4 (Location-Based)	91	86	92	94
YOLOv7-X (Overall)	85	-	-	-
YOLOv7-X (Location-Based)	95	93	95	96
YOLOv9c (Overall)	85	-	-	-
YOLOv9c (Location-Based)	96	93	95	98

Table 6 Precision (%) results for each model across all datasets.

Model	Average	Celsus Library	House of Virgin Mary	Ephesus Ancient City
YOLOv4 (Overall)	82	-	-	-
YOLOv4 (Location-Based)	89	87	88	91
YOLOv7-X (Overall)	83	-	-	-
YOLOv7-X (Location-Based)	93	91	93	97
YOLOv9c (Overall)	84	-	-	-
YOLOv9c (Location-Based)	93	92	94	94

Table 7 Recall (%) results for each model across all datasets.

Model	Average	Celsus Library	House of Virgin Mary	Ephesus Ancient City
YOLOv4 (Overall)	84	-	-	-
YOLOv4 (Location-Based)	90	90	86	94
YOLOv7-X (Overall)	86	-	-	-
YOLOv7-X (Location-Based)	94	91	95	96
YOLOv9c (Overall)	86	-	-	-
YOLOv9c (Location-Based)	95	92	95	97

Table 8 mAP (%) results for each model across all datasets.

Model	Average	Celsus Library	House of Virgin Mary	Ephesus Ancient City
YOLOv4 (Overall)	66	-	-	-
YOLOv4 (Location-Based)	68	65	68	70
YOLOv7-X (Overall)	68	-	-	-
YOLOv7-X (Location-Based)	69	68	69	71
YOLOv9c (Overall)	70	-	-	-
YOLOv9c (Location-Based)	71	69	71	72

Table 9 Performance metrics for YOLOv9c using 4-fold cross-validation.

Fold	Accuracy (%)	Precision (%)	Recall (%)	mAP (%)
Fold 1	93	91	93	71
Fold 2	93	91	93	**72**
Fold 3	**96**	**93**	**95**	71
Fold 4	90	90	92	70

DISCUSSION

The experimental results revealed notable strengths and weaknesses of the YOLOv4, YOLOv7-X, and YOLOv9c models in the context of historical artifact recognition. Among the tested models, YOLOv9c consistently demonstrated superior performance, particularly in location-based evaluations, achieving higher accuracy, precision, recall, and mAP metrics. This highlights its ability to adapt to the complexities of diverse datasets and to effectively identify artifacts in varied settings. However, the computational cost of YOLOv9c, especially during training on high-resolution images, was significantly higher compared to YOLOv4 and YOLOv7-X. On the other hand, while YOLOv4 was computationally less expensive, its performance metrics, particularly for precision and recall, were inferior to the other models. YOLOv7-X provided a balance between computational efficiency and performance, making it a viable alternative for resource-constrained environments.

During the training process, several challenges were observed. Overfitting was a notable issue, particularly for the location-based models, as the dataset size was limited for certain locations. This was mitigated using data augmentation techniques, though further work is required to enhance generalization. Additionally, the computational costs of training larger models, such as YOLOv9c, posed significant challenges, especially on high-resolution datasets. For future work, improving model generalizability by incorporating more diverse training datasets and exploring lightweight versions of the models without compromising performance are recommended. Furthermore, integrating transfer learning and advanced optimization techniques could reduce training time and computational costs while maintaining high accuracy and robustness.

CONCLUSION

This study explored the performance of YOLOv4, YOLOv7-X, and YOLOv9c models for the task of historical artifact recognition, with a particular focus on location-based segmentation to improve detection accuracy. Among the models, YOLOv9c demonstrated the best overall performance, achieving the highest accuracy, precision, recall, and mAP metrics, especially in location-based evaluations. This highlights its robustness and adaptability to diverse and complex datasets, making it a suitable choice for applications requiring high precision and reliability.

Despite its superior performance, the computational cost of YOLOv9c remains a challenge, particularly for training on high-resolution datasets. Conversely, YOLOv4 was computationally efficient but lagged behind in terms of accuracy and precision, while YOLOv7-X offered a balanced alternative between performance and computational demands. These findings emphasize the trade-offs between computational efficiency and detection accuracy in choosing an appropriate model for specific applications.

The integration of location-based segmentation significantly enhanced the detection accuracy by enabling the models to specialize in recognizing artifacts within geographically defined contexts. This approach, combined with advanced cross-validation techniques, ensured robust evaluation and selection of the best-performing models. Additionally, the development of a user-friendly application interface demonstrates the practical utility of the proposed system in providing real-time artifact recognition and historical information to users.

Future work will focus on addressing the limitations observed in this study, including mitigating overfitting through more diverse and extensive datasets and optimizing model architectures to reduce computational costs. The integration of transfer learning, advanced optimization techniques, and lightweight model architectures will be further explored to improve efficiency without compromising performance. Overall, this research demonstrates the potential of deep learning models like YOLOv9c in enhancing the recognition and interpretation of cultural heritage artifacts, paving the way for innovative applications in heritage conservation and tourism.

Acknowledgments

This research was financially supported by the Scientific and Technological Research Council of Türkiye (TÜBİTAK) under Grant No. 1919B012308335, as part of the 2209-A University Students Research Projects Support Program, 2023, 1st Term.

Availability of data and material

The data used in this study were sourced from specific cultural heritage sites and were subjected to preprocessing and data augmentation.

Conflicts of interest

The authors declare that there is no conflict of interest regarding the publication of this paper. Due to privacy concerns and the nature of the dataset, the data are not publicly available.

Ethical standard

The authors have no relevant financial or non-financial interests to disclose.

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How to cite this article: Şahin, A. T., Aktaş, E. and Kiran, H. E. Location-Based Technology for Real-Time Artifact Recognition in Businesses. *Information Technology in Economics and Business*, 2(1), 24-31, 2025.