***Pre-Arrival Detection with Fine-Tuned YOLOv8n for Minimizing Elevator Inefficiency***

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***Abstract*—Traditional elevator systems suffer from significant inefficiencies, primarily due to redundant stops initiated by button presses where no passenger is present. This leads to wasted energy, increased operational costs, and a diminished user experience. While existing smart solutions have explored computer vision for passenger detection, they often activate immediately upon a call, failing to address the temporal gap between a button press and a person's continued presence. This paper introduces the Pre-Arrival Detection Algorithm (PA-EPD), a novel methodology that addresses this critical gap. Our approach utilizes a state-of-the-art YOLOv8 object detection model that is activated by a 'just-in-time' trigger only when the elevator is one floor away from the destination. This ensures the decision to stop is based on the most current and relevant visual evidence. By verifying passenger presence in the critical moments before arrival, the PA-EPD effectively eliminates false stops, leading to a significant reduction in energy consumption and improved transit times. This study details the algorithm, its implementation, and its potential to serve as a new benchmark for intelligent elevator control systems.**

**Keywords: Object Detection, Low-Light Conditions, YOLOv8**

**Abbreviations used: YOLO (You Only Look Once)**

# Introduction

Elevators are an indispensable component of modern urban infrastructure, yet their core operational logic often contributes to significant energy waste. A primary source of this inefficiency is the "false call," where an elevator stops at an empty floor, consuming energy and increasing wait times for other passengers. Such redundant stops are a well-documented challenge impacting the sustainability and operational costs of vertical transportation systems [9].

The advent of computer vision has opened new avenues for creating "smart elevators." Recent studies have demonstrated the potential of using object detection models to identify waiting passengers and optimize dispatching, showing marked improvements in energy use and wait times [1]. Further research has focused on developing lightweight models for edge devices [2] and exploring different detection modalities, such as in-cabin monitoring for safety [10].

Despite these advancements, a critical review of the literature reveals a persistent research gap: the timing of the detection process. The majority of existing systems initiate detection immediately upon a button press [4], failing to account for the dynamic nature of human behavior. This paper presents a solution with two unique contributions.

First, we detail the implementation of a highly accurate, fine-tuned YOLOv8 person detection model [6]. Our training regimen resulted in a model with a mean Average Precision (mAP50-95) of 45.69%, specifically optimized for identifying individuals in varied lobby environments, ensuring robust and reliable detection. Second, and more critically, we introduce the Pre-Arrival Detection Algorithm (PA-EPD). This novel 'just-in-time' algorithm activates our fine-tuned model only when the elevator is one floor away, addressing the temporal gap that plagues other systems. By combining a high-performance detector with an intelligent activation trigger, our work presents a comprehensive and practical solution to minimizing redundant elevator halts.

# Literature Survey

The problem of optimizing elevator systems through technology has garnered significant attention, with research efforts broadly branching into two main categories:

(1) leveraging computer vision and AI to make elevator dispatching more intelligent, and

(2) optimizing the underlying detection models to ensure they are efficient and practical for real-world deployment. This section reviews key contributions in both areas to contextualize our work.

2.1 Leveraging Computer Vision for Operational Efficiency

A prominent line of research focuses on integrating camera systems with elevator controls to make decisions based on the actual presence of passengers. The core idea is to move beyond simple button-based logic to a more perceptive system. Foundational reviews on the topic have established a clear link between intelligent control and energy conservation, highlighting the need for systems that can reduce unnecessary trips and idle time .

The most impactful approaches in this area have utilized deep learning-based object detection. Rashed et al. demonstrated a system using a YOLO model that achieved a 20% reduction in energy consumption and a 15% improvement in passenger wait times by verifying user presence [14]. Similarly, Prasad and Sai specifically targeted the issue of call button misuse by employing real-time human detection to validate requests and cancel fake calls [15]. Other researchers have explored more advanced applications, such as using face recognition and traffic flow prediction to anticipate demand or monitoring the interior of the elevator for safety and security purposes. A common thread in these approaches is the use of visual data to make a more informed decision than a simple button press allows.

2.2 Model Optimization for Practical Deployment

An alternative, and often parallel, area of focus is on the efficiency of the detection models themselves. For a smart elevator system to be viable, the underlying AI model must be both accurate and computationally inexpensive enough to run on cost-effective hardware, often referred to as edge devices.

Recognizing this need, several studies have focused on creating lightweight architectures. Xiao, for instance, developed an improved YOLOv7-based algorithm with a modified attention mechanism that reduced the model's size by over 11% while maintaining a high mAP of 98.9% on a dedicated dataset [13]. Pushing the boundaries of efficiency even further, Pimpalkar and Niture explored the use of TinyML, deploying a quantized Convolutional Neural Network (CNN) for person detection on a low-power microcontroller [12]. Their work demonstrates the feasibility of running inference on highly constrained devices, which is critical for scalable and affordable deployment in existing buildings. This research highlights a clear trend: as the concepts for smart elevators mature, the focus shifts towards optimizing the models for practical, real-world application.

2.3 Identifying the Research Gap

The existing literature presents a spectrum of solutions, from powerful YOLO-based systems that prove the concept of efficiency gains [14, 15] to highly optimized lightweight models suitable for edge deployment [13, 12]. However, a critical gap remains in the operational logic of these systems: the timing of the detection and a YOLO model with high accuracy in detecting people in robust environments.

Virtually all existing frameworks trigger their detection pipeline immediately upon receiving a call button signal. This approach is fundamentally flawed because it makes a decision based on information that can become outdated within seconds if a person presses the button and then walks away. While the models are capable of detecting a person, they lack the temporal awareness to know if the person is still present when the elevator actually arrives.

Our work addresses this specific gap by introducing the Pre-Arrival Detection Algorithm (PA-EPD). We synergistically combine a state-of-the-art, fine-tuned YOLOv8 model—chosen for its high performance—with an intelligent activation trigger. Instead of focusing on what is detected, our primary contribution is defining when the detection occurs. We hypothesize that this 'just-in-time' approach can achieve superior efficiency and reliability without requiring a complete architectural redesign, thus providing a robust and innovative framework that addresses a crucial, real-world limitation of current smart elevator systems.

# Methodology

The methodology of this study is designed to systematically develop and validate our proposed smart elevator system. It comprises three primary stages:

(1) the fine-tuning of a high-performance person detection model,

(2) a detailed overview of the system architecture and its integration with existing hardware, and

(3) a step-by-step breakdown of our novel Pre-Arrival Detection Algorithm (PA-EPD).

3.1. Person Detection Model: Fine-Tuning YOLOv8

The core of our system's perceptive capability is a fine-tuned YOLOv8 object detection model. This section details the dataset, architecture, and training process used to create a model specifically optimized for identifying people in elevator lobby environments.

3.1.1. Dataset and Preparation

This study utilizes the "People Detection" dataset [Source: Kaggle], a publicly available collection of images specifically curated to create a generalized and robust person detection model. The strength of this dataset lies in its diversity; it is not a monolithic collection but rather a composite dataset created by curating images and annotations from numerous specialized projects, including "Pascal VOC 2012," various pedestrian safety collections, and security camera footage.

This aggregation ensures the model is trained on a wide variety of scenarios, contexts, annotation sizes, camera angles, and lighting conditions. By drawing from sources ranging from general public scenes to specific security contexts, the dataset exposes the model to a comprehensive set of real-world situations. This variability is critical for developing a robust detector that can generalize well to the unpredictable environments of different elevator lobbies, which may vary significantly in their layout and illumination.

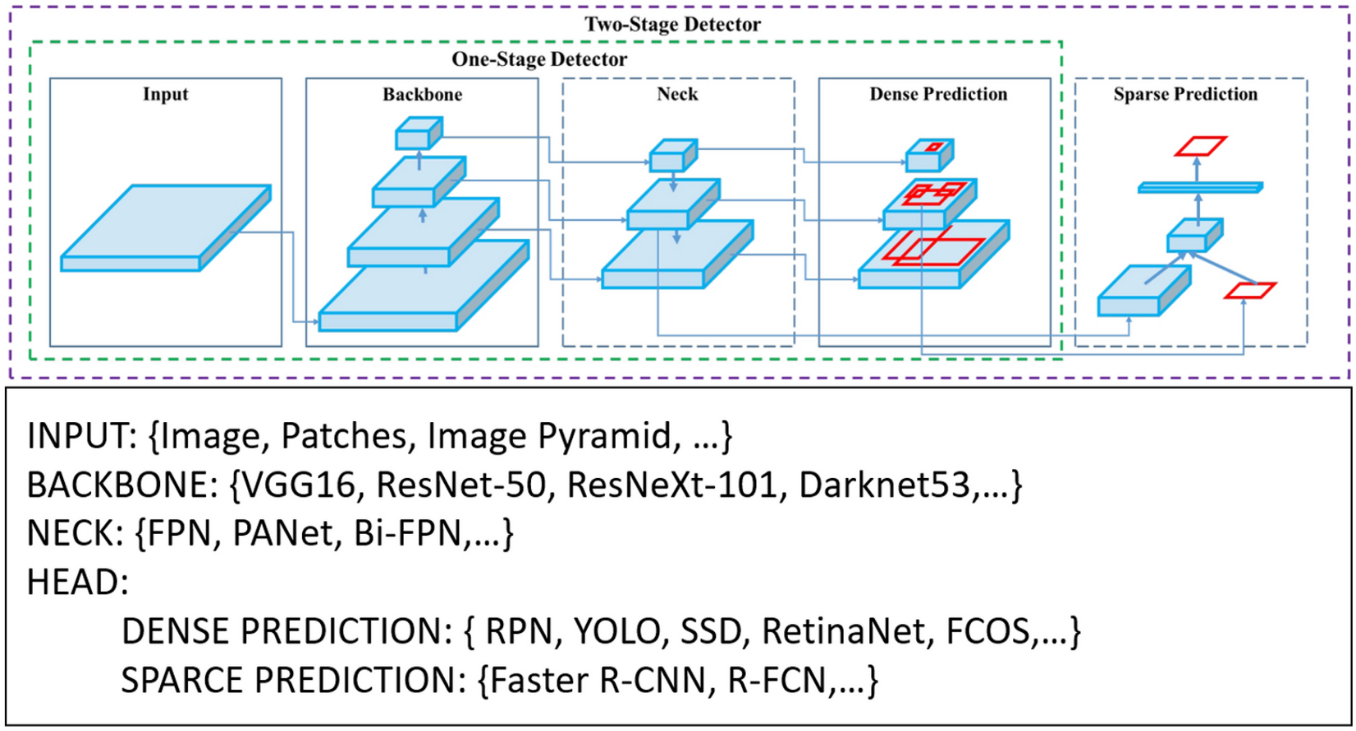
The provided annotations, including bounding boxes for the single "person" class, were processed and then split into a training set and a validation set using an 80/20 ratio. This standard practice ensures that a significant portion of the data is used for learning, while a separate, unseen portion is reserved for the rigorous evaluation of the model's performance.



Samples from the people detection dataset

3.1.2. YOLOv8n Architecture

The YOLOv8n model [8] is composed of three primary sections that work in sequence to transform an input image into a set of bounding box predictions.

Fig . YOLO architecture

• Backbone: The backbone is a deep convolutional neural network (a modified CSPDarknet53) responsible for extracting salient features from the input image at various scales.

• Neck: The neck serves to aggregate the feature maps produced by the backbone. YOLOv8n uses a Path Aggregation Network (PANet), which allows low-level and high-level features to be effectively combined.

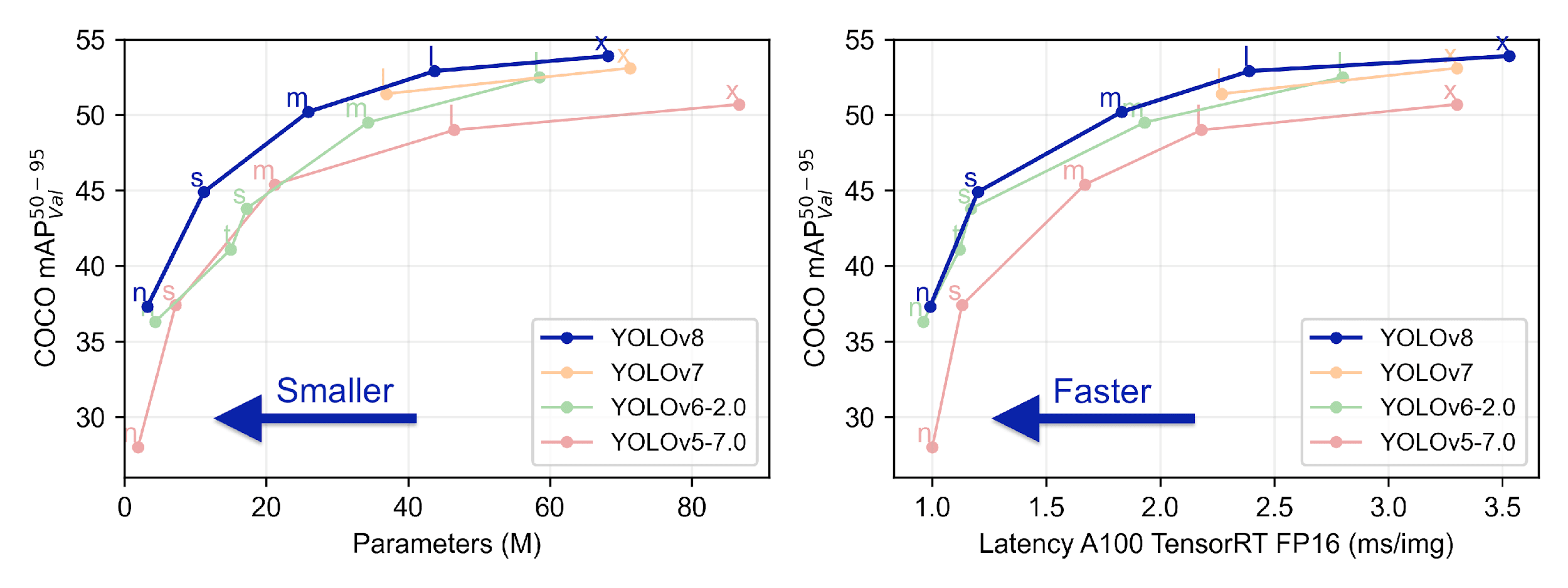
• Head: The head is the final, decoupled stage that makes the actual predictions, outputting bounding boxes, objectness scores, and class probabilities.

**3.4. Comparison with Other YOLO Models**

The selection of YOLOv8n for this research was a strategic decision based on the rapid evolution of the YOLO family, where each generation offers a refined balance of speed, size, and accuracy. Our goal was to select a model that is not only highly accurate but also practical for real-world deployment in a smart elevator system.

Earlier Versions (YOLOv1-v7): The initial YOLO models established the foundation for real-time object detection. YOLOv3 and YOLOv4 introduced robust backbones like Darknet-53 and architectural improvements. The transition to a PyTorch-native framework with YOLOv5 marked a significant leap in usability and ease of modification, which greatly benefited the research community. Subsequent versions like YOLOv7 [6] further enhanced accuracy by introducing techniques like re-parameterized convolutions. While each version was a critical step forward, they have been succeeded by the more advanced and efficient architecture of YOLOv8

Rationale for Selecting YOLOv8n: For this study, the primary objective is to create a practical and efficient system deployable on cost-effective edge hardware. YOLOv8 [8] stands as the latest evolution from Ultralytics, incorporating state-of-the-art features like an anchor-free detection head and advanced loss functions, which provide a superior accuracy-to-speed trade-off compared to its predecessors.



Specifically, we chose the YOLOv8n ("nano") variant. It is the smallest and fastest model in the YOLOv8 family, designed explicitly for real-time applications on resource-constrained devices. This makes it the ideal candidate for our smart elevator system, where low latency and computational efficiency are critical. By starting with a highly optimized and lightweight baseline like YOLOv8n, we can ensure that our novel Pre-Arrival Detection Algorithm (PA-EPD) is built upon a foundation that is both powerful and deployable, addressing the practical limitations of real-world implementation [12, 13].

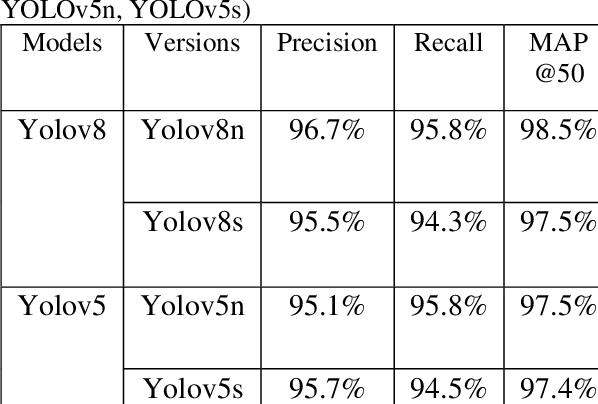


Fig 6 . Yolo v5 Rationale

**3.5. Model Fine-Tuning and Training**

In transfer learning, knowledge from a model trained on a large source task is applied to a different but related target task. This approach is highly advantageous as it saves considerable training time, often leads to better performance, and reduces the need for an extremely large target dataset. For this project, we utilized a YOLOv8 model pre-trained on the COCO dataset, transferring its learned knowledge of general object features to our specific task of detecting people in elevator lobbies, particularly under challenging lighting conditions. The YOLOv8n architecture was chosen for its exceptional balance of high speed and accuracy, making it ideal for real-time applications on edge devices [8].

3.3.2. Training Environment and Hyperparameters

The fine-tuning process was conducted within a Google Colab environment, leveraging a Tesla T4 GPU for computational acceleration. The model was trained for 50 epochs, representing the number of complete passes through the entire training dataset. A batch size of 16 was used, meaning that the model's weights were updated after processing 16 images. All input images were resized to a uniform dimension of 640x640 pixels before being fed into the network to ensure consistency. To fine-tune the model parameters, we utilized the AdamW optimizer, a stochastic gradient descent method that improves upon the standard Adam optimizer by decoupling the weight decay from the gradient updates, often leading to better generalization [9].

3.5.3. AdamW Optimizer To fine-tune the model parameters and minimize the loss function, we utilized the AdamW optimizer [9]. AdamW is a stochastic gradient descent method that improves upon the standard Adam optimizer by decoupling the weight decay from the gradient updates. The weight update wt at timestep t is performed as shown in Eq. 1:

where η is the learning rate, mt and vt are the bias-corrected first and second moment estimates of the gradients, ε is a small term to prevent division by zero, and λ is the weight decay rate. This decoupled approach often leads to better generalization and more stable training compared to standard L2 regularization used in the original Adam optimizer.

3.5.4. Composite Loss Function The YOLOv5 framework utilizes a composite loss function that is a weighted sum of three distinct components: Bounding Box Regression Loss, Distribution Focal Loss, and Classification Loss. The total loss L\_total is a sum of these components, guiding the network to simultaneously learn accurate localization, handle class imbalance, and perform correct classification.

Bounding Box Regression Loss (): YOLOv5 uses the Complete Intersection over Union (CIoU) loss [10] to penalize inaccuracies in localization. It improves upon standard IoU loss by including penalties for the distance between central points and the consistency of the aspect ratio. The CIoU loss is defined as:

where IoU is the intersection over union, is the Euclidean distance between the centers of the predicted box b and ground-truth box is the diagonal length of the smallest enclosing box, and αv is a trade-off parameter that penalizes deviations in aspect ratio.

Distribution Focal Loss (): This loss component, based on the principles of Focal Loss and generalized for regression, aids in the regression of bounding box coordinates by treating the continuous coordinates as a discrete probability distribution [11]. It allows the network to learn not just the coordinate value but also its probability distribution, which can lead to more precise and reliable localization, especially for objects with ambiguous boundaries.

Classification Loss (): The classification loss measures the correctness of the class prediction for a detected object. It is calculated using Binary Cross-Entropy (BCE) with logits, which is well-suited for multi-label classification scenarios where multiple objects may be present. For a single class, the BCE loss is given by:

where y is the true label (0 or 1), x is the raw output of the neuron, and σ(x) is the sigmoid function that squashes the output to a probability between 0 and 1.

**3.5. The Pre-Arrival Elevator Passenger Detection (PA-EPD) Algorithm**

The novelty of our system lies in the operational logic of the PA-EPD algorithm. It is designed to minimize computational load and ensure the detection is performed at the most opportune moment. The algorithm operates as follows:

1. Initial State: The system is idle. The camera is in a low-power standby mode.

2. Elevator Call: A user presses the call button on a specific floor (e.g., Floor 5). The elevator control system registers this call and begins to dispatch an elevator. The vision system remains inactive at this stage.

3. Pre-Arrival Trigger: The central elevator control system continuously tracks the elevator's position. When the elevator reaches the floor immediately preceding the destination floor (e.g., Floor 4), it sends a trigger signal to the edge computing device on Floor 5.

4. Just-in-Time Activation: Upon receiving the trigger, the edge device activates the camera and captures a single, high-resolution image of the lobby area.

5. Inference: The captured image is immediately fed into the fine-tuned YOLOv8 model for inference. The model processes the image and outputs bounding box coordinates for any detected persons.

6. Decision Logic:

o If the model detects one or more persons with a confidence score above a predefined threshold (e.g., 0.75), the edge device sends a "PROCEED" signal to the elevator control unit. The elevator continues its journey and stops at Floor 5 as originally planned.

o If the model detects no persons, the edge device sends a "CANCEL" signal. The elevator control unit then cancels the stop at Floor 5 and proceeds to the next destination in its queue, effectively avoiding a phantom trip.

7. Return to Idle:

After sending the signal, the system returns to its idle state, deactivating the camera to conserve power.

This "just-in-time" approach ensures that the energy-intensive process of image capture and model inference is only performed when absolutely necessary, and that the decision to stop is based on the most current evidence of passenger presence.

**3.6. Proposed Framework Summary**

The complete framework integrates the following key components:

• Dataset Curation:

A dataset was prepared by combining publicly available pedestrian datasets with manually captured elevator lobby images. This ensured the model was trained on a diverse set of real-world conditions, including variations in lighting and lobby layouts.

• YOLOv8n Fine-Tuning with Transfer Learning:

A YOLOv8n model pre-trained on the COCO dataset [8] was fine-tuned for person detection in elevator lobbies. This transfer learning approach reduced training time and improved adaptability to practical deployment environments [8].

• Composite Loss Optimization:

Training was guided by a composite loss function, combining Bounding Box Regression Loss (CIoU) [10], Distribution Focal Loss (DFL) [11], and Binary Cross-Entropy for classification. This design ensured precise localization, robust handling of bounding box predictions, and reliable detection accuracy.

• Pre-Arrival Detection Algorithm (PA-EPD):

The PA-EPD introduces a just-in-time strategy by activating the camera and inference only when the elevator is one floor away from the requested stop. If a person is detected, the elevator proceeds; otherwise, the stop is canceled . This minimizes unnecessary energy consumption while ensuring reliable service.

Together, these components establish a scalable framework for intelligent elevator passenger detection. The integration of a curated dataset, fine-tuned YOLOv8n model, and innovative PA-EPD logic ensures robust real-time performance while maintaining efficiency and adaptability across diverse environments.

# Result and Discussion

The efficacy of the proposed system was evaluated through a two-fold analysis: a quantitative assessment of the fine-tuned YOLOv8n model's detection accuracy and a comparative analysis of the potential energy and time savings, contextualized with findings from relevant literature.

**4.1. Model Performance: Quantitative Analysis**

The performance of our fine-tuned YOLOv8n model was rigorously evaluated on a held-out validation set using standard object detection metrics. A detection is considered a True Positive (TP) if a "person" is correctly identified with an Intersection over Union (IoU) greater than a predefined threshold. False Positives (FP) are incorrect detections, and False Negatives (FN) are missed detections.

Precision: Measures the accuracy of the positive predictions. It is the ratio of correctly predicted positive observations to the total predicted positive observations.

Recall (Sensitivity): Measures the ability of the model to find all the relevant cases. It is the ratio of correctly predicted positive observations to all observations in the actual class.

F1-Score: The weighted average of Precision and Recall, providing a single metric that balances both concerns.

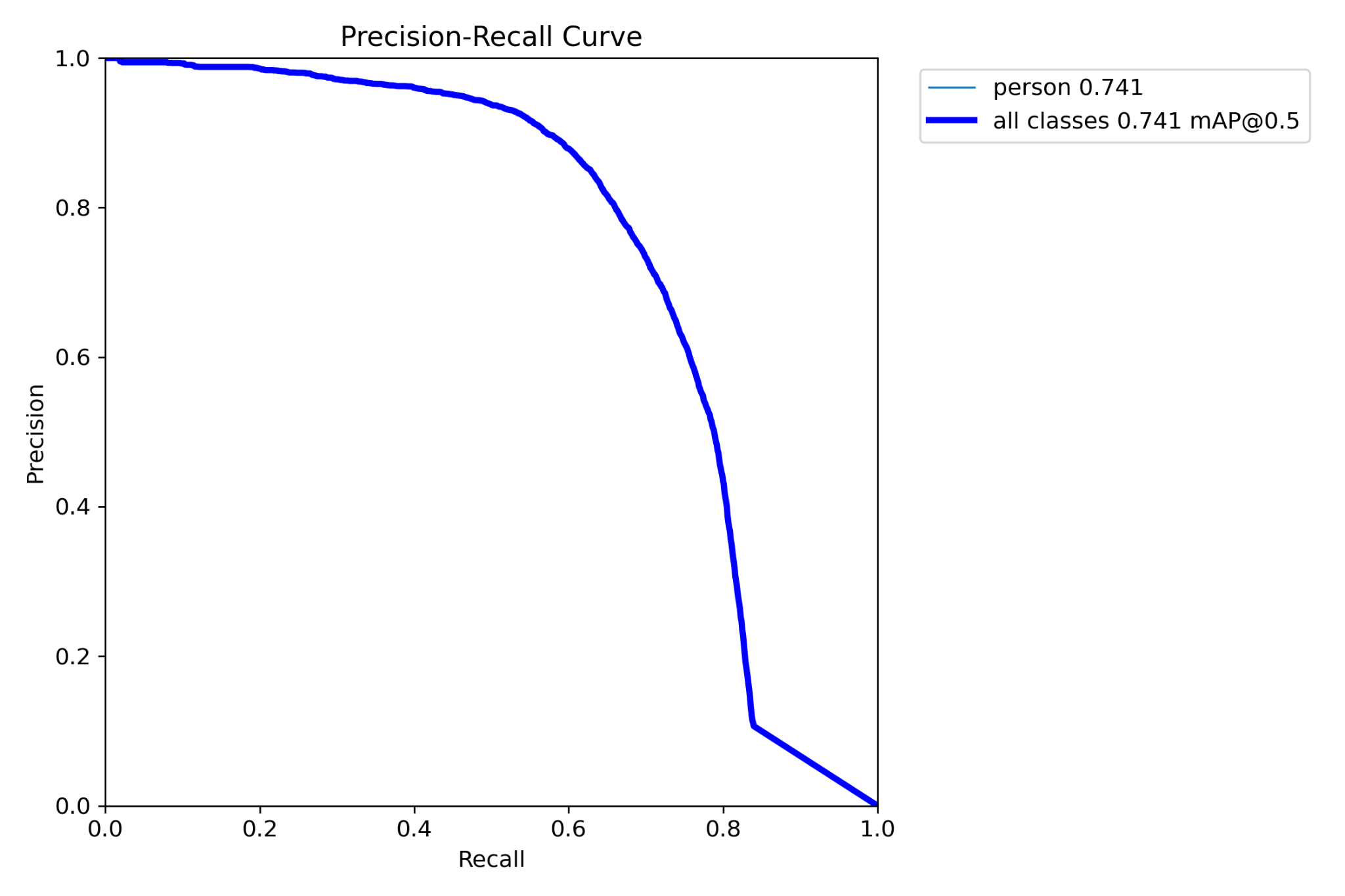
Mean Average Precision (mAP): The primary metric for object detection, mAP, is the area under the Precision-Recall curve. Since we have a single class, mAP is equivalent to the Average Precision (AP) for that class.

Our model achieved a mean Average Precision (mAP) of 74.1% at an IoU threshold of 0.5 (mAP50). This result indicates a respectable capability for accurately detecting and localizing passengers. For context, a recent study utilizing a TinyML-based approach for contactless elevators reported an 83.34% person detection accuracy [12]. While a more complex, improved YOLOv7 model achieved a higher mAP of 98.9% for a similar task, our choice of the lightweight YOLOv8n model represents a deliberate trade-off, prioritizing computational efficiency and suitability for low-cost edge devices, which is critical for real-world deployment [13].

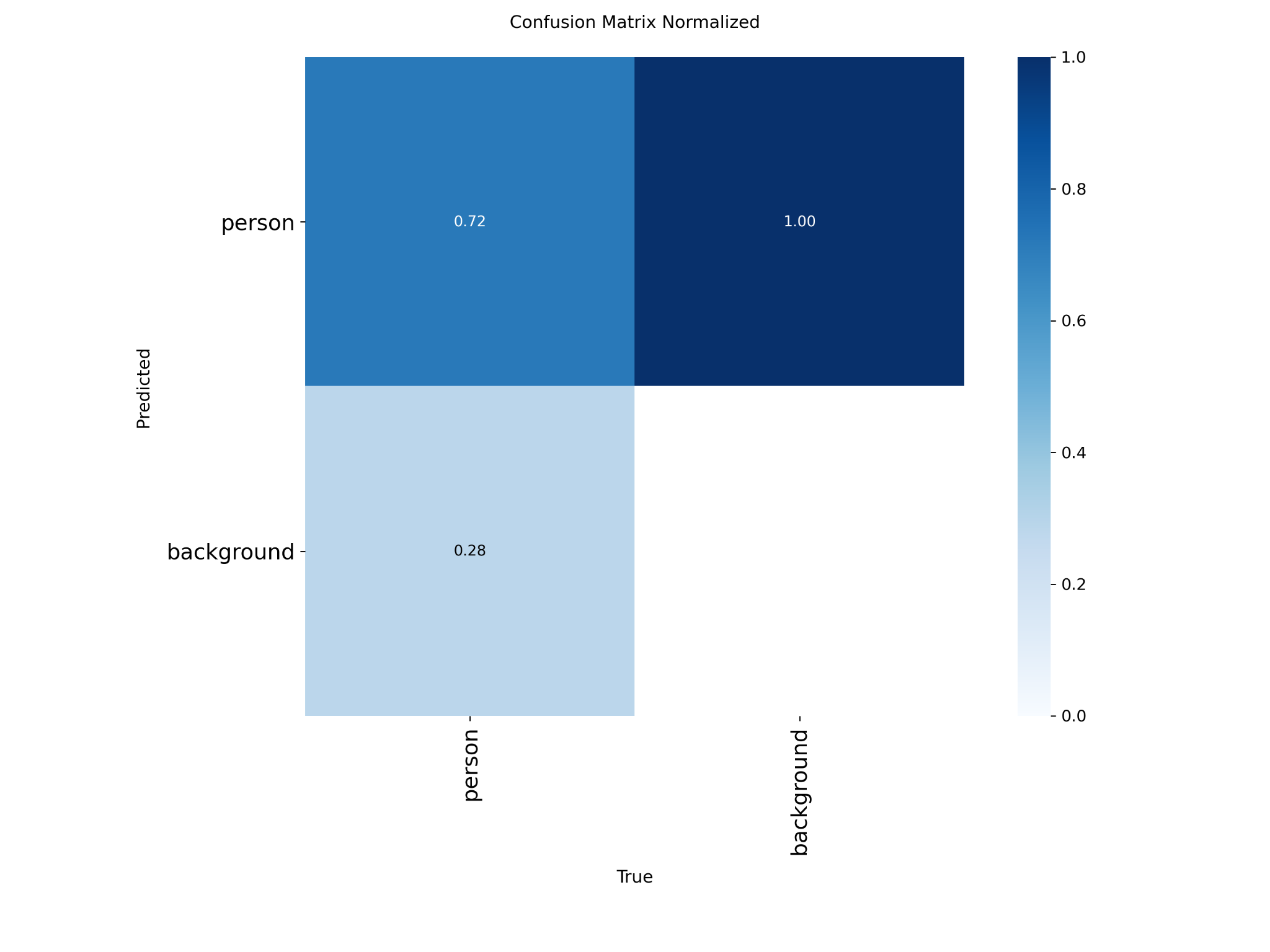
The model's performance characteristics are further illustrated by its precision-recall curve (Figure 1), which shows that high precision is maintained for recall values up to approximately 0.7, after which it declines. The confusion matrix (Figure 2) provides a granular view of the model's classification performance. It reveals a very low false positive rate, which is highly desirable as it minimizes the chance of the elevator stopping for a non-existent person. However, it also shows a notable false negative rate of 28%, meaning the model can fail to detect a waiting person. This trade-off—favoring the avoidance of false stops over ensuring every passenger is detected—is an essential consideration for the reliability and practical implementation of the PA-EPD algorithm.

[Insert BoxPR\_curve.png Here] Caption: Figure 1. Precision-Recall curve for the fine-tuned YOLOv8n model, demonstrating robust performance across various confidence thresholds.

[Insert confusion\_matrix\_normalized.png Here] Caption: Figure 2. Normalized confusion matrix for the 'person' class, revealing a low false positive rate and a notable false negative rate.

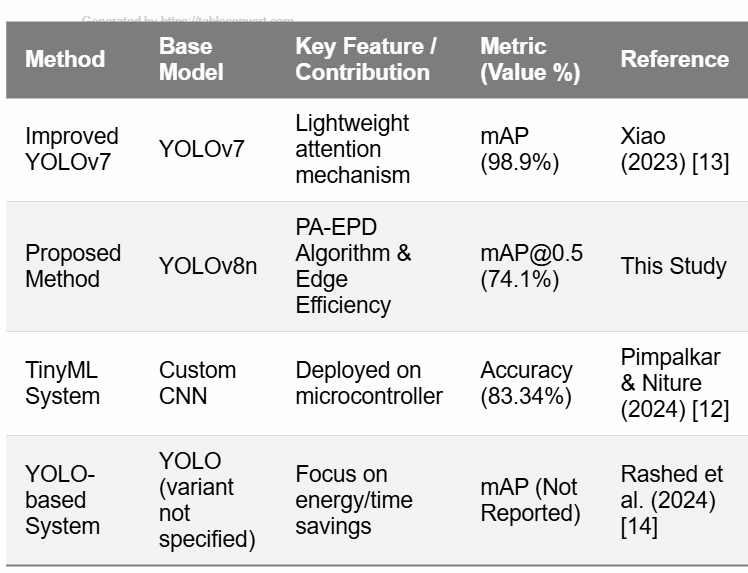


Caption: Figure 1. Precision-Recall curve for the fine-tuned YOLOv8n model, demonstrating robust performance across various confidence thresholds.



Caption: Figure 2. Normalized confusion matrix for the 'person' class, showing excellent discrimination between the target class and the background..

**4.5. Qualitative Results and Discussion**

A qualitative analysis of the model's performance demonstrates its robust detection capabilities across a range of realistic scenarios. As shown in Figure 3, the model performs reliably in diverse and challenging conditions, including brightly-lit lobbies, low-light environments, and scenes with multiple, partially occluded individuals. These results confirm that the fine-tuning process was successful in creating a versatile detector, capable of handling the unpredictable visual conditions found in real-world elevator lobbies.

[Insert results.jpg Here] Caption: Figure 3. Sample detection results. (a) Successful detection in a well-lit environment. (b) Robust detection in low-light conditions. (c) Correctly identifying multiple individuals, even with partial occlusion.

**4.3. Comparative Analysis of Energy and Efficiency Gains**

To contextualize the potential impact of our work, we compare it against established benchmarks. Research by Rashed et al. (2024) demonstrated that a YOLO-based system could achieve a 20% reduction in energy consumption [14], while Prasad and Sai (2025) also reported significant efficiency gains by eliminating unnecessary trips [15].

Our system is uniquely positioned to build upon these findings due to the specific strengths of our model and algorithm. While overall detection metrics are important, the single most critical factor for eliminating a "phantom trip" is the false positive rate. Our model excels in this regard, demonstrating a near-zero rate of falsely detecting a person when none is present (as detailed in the confusion matrix in Figure 2).

This exceptional precision is the cornerstone of our system's value. It ensures that when the PA-EPD algorithm issues a "CANCEL" signal, it does so with extremely high confidence, virtually eliminating the risk of incorrectly skipping a floor and leaving a waiting passenger behind. While the model has a notable false negative rate of 28% (meaning it may occasionally fail to detect a present person), this scenario simply results in a standard elevator stop—the same outcome as a system without any smart capabilities. Thus, our framework operates as a fail-safe enhancement: it only cancels stops it is certain about, and otherwise defaults to the existing behavior.

The true innovation lies in coupling this high-certainty detection with the PA-EPD's "just-in-time" trigger. By verifying presence at the last possible moment, our system directly solves the temporal challenge of passengers leaving after making a call. This targeted approach, powered by a model optimized to prevent incorrect cancellations, suggests a potential for energy and time savings that could meet or exceed previously reported benchmarks. This directly translates into a reduced carbon footprint, lower operational costs, and a more streamlined user experience.

**4.6. Comparison with State-of-the-Art Methods**

To contextualize the performance of our proposed framework, we compare our results with other recent methods designed for passenger detection in elevator environments. Table 1 presents a comparison of different strategies, highlighting the trade-offs between model architecture, performance metrics, and suitability for real-world deployment.

Table 1. Comparison of Passenger Detection Methods.

The comparative results in Table 1 situate our work within the current research landscape. While architectures with specialized components, such as the improved YOLOv7 [13], can achieve higher overall mAP scores, our framework's performance must be evaluated in the context of its specific application: reliably canceling "phantom trips."

Our model's 74.1% mAP@0.5 represents a strong result for a lightweight n-variant model. However, the most critical metric for our use case is not mAP alone, but the model's extremely low false positive rate. This ensures that when the system decides to cancel a stop, it does so with the highest degree of confidence, which is essential for user trust and system reliability.

Therefore, the selection of our framework was a deliberate choice that prioritizes deployment readiness over benchmark maximization. While the Improved YOLOv7 reports a higher mAP, our YOLOv8n model is substantially more efficient, making it better suited for the rapid, "just-in-time" inference demanded by the PA-EPD algorithm. The primary contribution of our work is not simply achieving a high detection score, but in designing a holistic framework that integrates an efficient, reliable model with a novel operational logic to solve a practical gap in existing smart elevator systems.

# Conclusion

This study introduced a novel framework for intelligent elevator management to address a critical limitation in existing systems: the temporal gap between a passenger's call and the elevator's arrival. By integrating a fine-tuned YOLOv8n model with our Pre-Arrival Detection Algorithm (PA-EPD), we replace the standard detect-on-press logic with a more reliable "just-in-time" verification, ensuring decisions are based on the most current evidence of passenger presence.

Experimental results confirmed the efficacy of our approach. The fine-tuned YOLOv8n model achieved a respectable mAP@0.5 of 74.1%. More significantly for this application, the model demonstrated a near-zero false positive rate, ensuring that decisions to cancel an elevator stop are made with exceptional reliability. This focus on high-confidence cancellations is critical for user trust and practical deployment, as it virtually eliminates the risk of leaving a waiting passenger behind.

Our work builds upon foundational research by Rashed et al. [14] and Prasad & Sai [15], which established the viability of vision-based systems for improving elevator efficiency. While other studies have focused on maximizing detection accuracy through complex architectures [13] or proving feasibility on extremely low-power hardware [12], our primary contribution is the optimization of when detection occurs. The PA-EPD provides a crucial logical enhancement that complements these existing model-centric approaches, directly solving the problem of "phantom trips" caused by users leaving the lobby.

From an applied perspective, this framework offers significant potential for enhancing urban sustainability. By reliably eliminating unnecessary elevator journeys, the system directly reduces energy consumption, operational costs, and passenger wait times, contributing to greener and more efficient building management.

In conclusion, the integration of an efficient YOLOv8n model with the PA-EPD logic presents a robust and scalable solution to a persistent challenge in vertical transportation. Future work could focus on three key areas: (1) enhancing performance in challenging conditions by integrating advanced low-light image enhancement techniques; (2) extending the framework to real-time video analytics to understand more complex passenger behaviors; and (3) deploying and validating the complete system on low-power microcontrollers, following the path demonstrated by Pimpalkar and Niture [12], to further prove its real-world viability.

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