

Non-Contact Overloading Detection System for Public Utility Buses Using Yolov8 Algorithm

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Abstract

Overloading in public utility buses remains a persistent transportation safety and regulatory problem, particularly in urban environments, where monitoring is often conducted through manual inspection. This study developed and evaluated a non-contact overloading detection system for public utility buses using the YOLOv8 object detection algorithm, Raspberry Pi 4, camera module, GPS, and real-time alert transmission. The study employed a descriptive-developmental quantitative design and Agile software development methodology. Fifty respondents participated in the evaluation, consisting of 44 passengers and 6 authorities. System performance was assessed through controlled trials, ISO/IEC 25010-based survey questionnaires, and object detection metrics, including precision, recall, and mean average precision (mAP). Test trials showed detection accuracies ranging from 67% to 82%, with one case of over-detection. Real-time processing achieved an average speed of 0.04 to 0.09 seconds per frame. Survey-based evaluation indicated high acceptance across hardware detection (overall mean = 4.40), alert system performance (overall mean = 4.41), and real-world system performance (overall mean = 4.37). ISO/IEC 25010 evaluation also showed strong results in usability (4.46), security (4.44), maintainability (4.44), reliability (4.37), efficiency (4.37), and functionality (4.19). YOLOv8 performance metrics reported precision = 0.94, recall = 0.91, mAP50 = 0.95, and mAP50-95 = 0.88. Findings indicate that the proposed system is feasible for real-time overloading monitoring, though performance remains sensitive to occlusion, lighting, crowd density, and network stability.

Keywords: computer vision, YOLOv8, public utility buses, overloading detection, Raspberry Pi, real-time monitoring

Introduction

Overloading in public utility buses (PUBs) continues to present safety hazards, operational inefficiencies, and compliance challenges in urban transportation systems. In Calamba, Laguna, overloading detection is commonly performed through manual observation by traffic enforcers stationed at terminals or checkpoints. Such methods are time-consuming, subjective, and prone to human error, which may result in inconsistent implementation of passenger capacity regulations.

The growing availability of computer vision, embedded systems, and real-time monitoring technologies offers a practical alternative to manual passenger monitoring. Recent studies have shown the increasing use of deep learning models, particularly the YOLO family of algorithms, in transportation and surveillance applications because of their speed and detection accuracy. YOLO-based systems have been applied in vehicle tracking, smart traffic monitoring, passenger counting, and urban surveillance contexts. These studies suggest that real-time detection models can support transportation management by automating visual monitoring tasks.

This study proposes a Non-Contact Overloading Detection System for Public Utility Buses Using the YOLOv8 Algorithm. The system uses a camera to capture live bus interior footage, applies YOLOv8 to detect and count passengers, and transmits alerts with timestamp and location data when overloading is detected. A Raspberry Pi 4 serves as the embedded processing unit, while GPS and MQTT-based communication support remote monitoring and notification.

The study is anchored in Systems Theory, Human Factors Engineering Theory, and the Technology Acceptance Model (TAM). Systems Theory frames public transportation as an interdependent system in which monitoring technology affects safety, compliance, and operational efficiency. Human Factors Engineering emphasizes usability, accessibility, and reduced user error in real-world deployment. TAM supports the expectation that perceived usefulness and ease of use influence adoption by transport regulators and operators.

Despite the growing use of YOLO in real-time detection applications, a gap remains in the use of such systems for direct overloading detection and automated enforcement support in public transportation. Many existing studies primarily focus on passenger counting or object detection, with limited integration of real-time alerts, event logging, and transportation monitoring workflows. To address this gap, the present study develops and evaluates a real-time, non-contact monitoring system designed for practical implementation in public utility buses.

Specifically, the study aimed to:

1. Create and build a hardware-based system for overloading detection through real-time computer vision, passenger detection, and embedded data processing.
2. Establish an alert system that automatically notifies stakeholders in case of overloading.
3. Evaluate the system's real-world performance in terms of detection accuracy, dependability, and responsiveness.
4. Determine the system's effectiveness using ISO/IEC 25010 quality standards.
5. Identify possible system enhancements and future development directions.

Methodology

Research Design

This study employed a descriptive-developmental quantitative research design. The descriptive component was used to evaluate system performance, user perceptions, and quality characteristics, while the developmental component documented the design, construction, testing, and refinement of the proposed system. The system was developed using the Agile software development methodology, which enabled iterative improvements in passenger detection, alert transmission, and monitoring functionalities throughout the development process.

Locale and Participants

The study focused on the Calamba, Laguna, transport context, particularly on routes with high passenger volume. Respondents were selected from two stakeholder groups directly involved in or affected by bus overloading: passengers and transport authorities. A total of 50 respondents participated, consisting of 44 passengers and 6 authorities.

Purposive sampling was used because participants were selected based on their direct relevance to public transportation operations and regulatory enforcement. Although Yamane's formula was discussed in the thesis, the final sample depended on participant availability and willingness.

System Architecture and Components

The proposed system consists of the following hardware and software components:

- Raspberry Pi 4 Model B (4 GB RAM) as the main embedded processor
- Camera module with wide-angle view for live bus interior monitoring
- GPS module for real-time location tracking
- MicroSD storage for operating system, models, and logs
- Raspberry Pi OS as the operating system
- Python as the primary programming language
- OpenCV for video capture and processing
- Ultralytics YOLOv8 for object detection
- MQTT for alert transmission
- Flask-based interface and mobile monitoring application for display and notification

The camera captures live frames inside the bus. The Raspberry Pi processes the video using YOLOv8 to detect and count passengers. If the detected count exceeds the allowable limit, the system generates an overload alert with timestamp, location coordinates, and bus information, which is then transmitted to the monitoring interface.

Data Gathering Tools

Data were collected using the following tools:

- Survey questionnaires aligned with ISO/IEC 25010 quality criteria
- Interviews with stakeholders and technical participants
- Field observations during controlled and simulated testing
- System logs documenting detection output, speed, and alert generation

The five-point Likert scale used in the study ranged from 1 = Strongly Disagree to 5 = Strongly Agree.

Data Analysis

Descriptive statistics, particularly the mean, were used to summarize survey responses. System effectiveness was also examined using object detection metrics:

- Precision
- Recall

- Mean Average Precision (mAP)

These metrics were used to evaluate the YOLOv8 model's passenger detection performance. Results from system testing and surveys were compared and interpreted according to the stated study objectives.

Results and Discussion

System Test Trials

The system was tested under varying conditions to assess passenger detection accuracy.

Table 1

Sample Accuracy Test Results

Trial	Actual Count	Detected	Accuracy	Remarks
1	17	14	82%	Several passengers at the back were not detected due to distance and occlusion.
2	12	8	67%	Four illustrated passengers were missed; cartoon style reduced detection consistency.
3	13	14	N/A	System detected more people than present, indicating false positives in the simulated environment.
4	16	11	69%	Multiple participants were not detected due to lighting and crowd arrangement issues.

The results show that the system can detect passengers under test conditions, but performance varies depending on scene complexity, visual style, lighting, and occlusion. These findings are consistent with known limitations in real-time object detection, particularly in crowded environments and constrained camera views.

Hardware-Based Detection System

The respondents evaluated the hardware-based detection system positively.

Table 2

Hardware Detection

Statement	Mean Verbal Interpretation
The system accurately detects passenger count.	4.50 Strongly Agree
Hardware components function properly.	4.46 Strongly Agree
System operates reliably under bus conditions.	4.40 Strongly Agree
System works consistently under varying loads.	4.34 Agree
Easy to implement and integrate.	4.32 Agree
Overall	4.40 Strongly Agree

Respondents strongly agreed that the system accurately detects passenger count and that the hardware components function properly. This suggests that the combination of camera input, embedded processing, and YOLOv8 detection is sufficiently robust for pilot deployment. However, the trial results show that perceived effectiveness exceeds actual test accuracy in some scenes, suggesting that stakeholder acceptance may reflect both system promise and observed performance.

Alert System Performance

The automatic alert system also received favorable evaluations.

Table 3

Alert System

Statement	Mean Verbal Interpretation
Alerts are transmitted to authorities.	4.48 Strongly Agree
Alert system is reliable and consistent.	4.44 Strongly Agree
Alert interface is easy to use.	4.42 Strongly Agree
System integrates smoothly with existing workflow.	4.36 Agree
System can be monitored remotely.	4.32 Agree
Overall	4.41 Strongly Agree

The findings indicate that the system can support real-time wireless alert transmission and remote monitoring. Alert reliability is an important contribution because detection alone is insufficient without actionable communication. Still, the study notes that GPS accuracy and network connectivity can affect timely delivery and precise location reporting.

Real-World System Performance

The system was further evaluated in terms of passenger detection accuracy, dependability, and alert responsiveness.

Table 4
System Performance

Statement	Mean	Verbal Interpretation
System accurately detects passengers in real-world conditions.	4.44	Strongly Agree
System performs reliably during bus operation.	4.40	Strongly Agree
Alert response is prompt and effective.	4.38	Strongly Agree
System maintains consistency under peak loads.	4.34	Agree
System is adaptable to different bus routes.	4.32	Agree
Overall	4.37	Strongly Agree

Real-time processing speed averaged 0.04 to 0.09 seconds per frame, supporting timely detection and alert generation. These results suggest that the system is capable of near-real-time performance on embedded hardware. However, reduced accuracy in crowded and poorly lit scenes indicates that speed does not necessarily guarantee consistent detection quality.

ISO/IEC 25010 Evaluation

The system was assessed using ISO/IEC 25010 quality criteria.

Table 5
Evaluation Summary of the YOLOv8-Based Bus Overloading Detection System (ISO/IEC 25010)

Criteria Mean Verbal Interpretation

Usability	4.46	Strongly Agree
Security	4.44	Strongly Agree
Reliability	4.37	Strongly Agree
Efficiency	4.37	Strongly Agree
Functionality	4.19	Agree
Maintainability	4.44	Strongly Agree
Grand Mean	4.44	Strongly Agree

The system performed strongly in usability, security, and maintainability, while functionality received a slightly lower but still positive evaluation. This pattern suggests that users found the system understandable and manageable even where detection performance was not perfect. The study also notes possible improvements such as better documentation, clearer interface elements, and stronger authentication measures.

YOLOv8 Performance Metrics

The study reported the following object detection metrics for the YOLOv8 model:

Table 6
YOLOv8 Performance Evaluation

Metric	Score
Precision	0.94
Recall	0.91
mAP50	0.95
mAP50-95	0.88

These metrics indicate strong model performance overall. High precision suggests relatively few false positives, while high recall indicates strong passenger coverage in many scenes. However, these metric values appear more favorable than the trial-level detection accuracies shown earlier, which implies that controlled model evaluation and actual bus-like testing conditions differ. This difference is important: model

performance in validation settings does not always transfer directly to real-world crowded interiors with occlusion, glare, motion, and suboptimal camera placement.

Discussion

Taken together, the findings support the feasibility of a non-contact overloading detection system based on YOLOv8 and Raspberry Pi 4. The system demonstrates strong potential for real-time monitoring, automated alert generation, and integration with transport oversight workflows. The positive ISO/IEC 25010 results further suggest that the system is usable, maintainable, and acceptable to intended stakeholders.

At the same time, the findings reveal practical limitations. Detection performance is sensitive to environmental conditions such as low light, crowd density, back-area seating visibility, and overlapping passengers. Network quality and GPS precision also affect the reliability of remote alerts. These limitations are significant because overloading detection in public transport occurs in highly dynamic and visually complex settings.

The study therefore contributes a workable prototype and an applied evaluation, while also showing that deployment-ready transport vision systems require more than strong algorithm metrics. Real-world robustness depends on training diversity, camera design, placement strategy, and communication reliability.

CONCLUSIONS

This study developed and evaluated a Non-Contact Overloading Detection System for Public Utility Buses Using the YOLOv8 Algorithm. The system successfully integrated computer vision, embedded processing, GPS tracking, and real-time alert transmission into a single monitoring platform for detecting passenger overloading.

Findings show that the system is capable of real-time passenger monitoring and automated alert generation, with positive evaluations from passengers and authorities across hardware detection, system performance, and ISO/IEC 25010 quality dimensions. YOLOv8 model metrics were high, and processing speed was fast enough for practical monitoring tasks. These results indicate that the proposed system is feasible as a support tool for transportation safety and regulatory compliance.

However, actual trial results also showed that performance is affected by occlusion, lighting variation, crowd arrangement, and occasional false detections. GPS accuracy and network dependence may further influence operational reliability. Thus, while the system is promising and functional, further optimization is needed before larger-scale deployment.

Overall, the study demonstrates that combining YOLOv8 with embedded hardware can produce a practical, non-intrusive, and scalable solution for monitoring overloading in public utility buses.

AI DECLARATION

Artificial intelligence (AI) tools, specifically ChatGPT by OpenAI, were used solely to assist in paraphrasing selected sections, improving grammar, and enhancing the clarity of the manuscript. The AI tool was not used to generate the research topic, methodology, data collection, analysis, results, discussions, or conclusions. All content was reviewed, verified, and approved by the authors, who take full responsibility for the accuracy, originality, and integrity of this research.

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