ISSN 2958-0846 eISSN 2958-0854 Journal of Problems in Computer Science and Information Technologies №1 (2) 2024 https://jpcsip.kaznu.kz

IRSTI 28.23.29 https://doi.org/10.26577/jpcsit2024020101

A.R. Rakhymova[1], A.B. Mussina[2*], S.S. Aubakirov[1], P. Trigo[3]

[1]Astana IT University, Astana, Kazakhstan
[2]Al-Farabi Kazakh National University, Almaty, Kazakhstan
[3]Instituto Superior de Engenharia de Lisboa, Lisbon, Portugal
*e-mail: mussina.aigerim95@gmail.com

DEVELOPMENT OF AN INTELLIGENT PASSENGER COUNTING SYSTEM FOR ENHANCING PUBLIC TRANSPORT EFFICIENCY AND OPTIMIZING ROUTE NETWORKS

Abstract. This study introduces a project aimed at the design and deployment of an intelligent passenger counting system for public transport. The objective is to enhance fare evasion control and reduce financial losses for transport operators through automated tracking of passenger entries and exits. The system employs the YOLO and DeepSORT algorithms, known for their high accuracy in identifying and monitoring passengers within complex environments. Experimental investigations reveal the critical role of camera type and positioning on system efficacy; notably, utilizing USB cameras over IP cameras enhances frame processing speed and overall system performance. However, testing has identified areas for improvement, particularly in managing group movements, minimizing frame loss, and increasing real-time accuracy. Future development efforts will focus on integrating depth sensors and crafting sophisticated data analysis algorithms to refine passenger counting precision during peak traffic periods. Anticipated outcomes of this project include optimized transport routes and schedules, improved management of passenger flows, heightened passenger satisfaction, and effective fare evasion prevention.

Key words: passenger counting, computer vision, YOLO, DeepSORT, video analysis

1 Introduction

The project aims to develop an intelligent passenger counting system for buses employing detection-based tracking technology. This is crucial to optimize the route network and improve the operational efficiency of public transport. To achieve this goal, scientific research and the development or adaptation of existing computer vision and machine learning methods are required. The obtained data regarding bus journeys and occupancy enable the analysis of population movement, the nature of travel, and the demand for public transportation. This system is also vital for optimizing bus routes and schedules, reducing congestion, shortening travel time, and improving overall public transport efficiency. This ensures effective measures against fare evasion, provides controllers with up-to-date data for prompt identification of violators, and minimizes financial losses for transport companies.

The functionality of the passenger counting system extends beyond simple tallying, offering transport operators and surveillance systems critical insights into bus occupancy levels. Such data enables the real-time modification of schedules and routes in response to immediate demand, the optimization of vehicle allocation per route, and the enhancement of the overall efficiency of the transport network.

Moreover, disseminating real-time information about bus boarding via mobile applications and digital displays at bus stops will significantly improve passenger convenience and satisfaction. This initiative enables travelers to plan their journeys, avoid crowded buses, and optimize their time utilization.

The implementation of these passenger counters will further aid in the effective management of passenger flow during peak times, diminish waiting periods for transportation, and elevate the overall service quality. These systems are a crucial component of a contemporary, sustainable, smart public transportation strategy, aiming to make urban commuting more comfortable and environmentally friendly.

This data harbors the potential for extensive research in the fields of sociology and urban planning. The project adopts a multidisciplinary methodology, integrating aspects of computer science, transportation logistics, data analysis, artificial intelligence, and social sciences. As a result, it is positioned to significantly contribute to the sustainable development of public transport and urban mobility systems. By addressing current challenges and offering scientifically grounded enhancements, the project aspires to provide more convenient and efficient passenger services, thereby making a substantial contribution to the progress of urban transportation systems.

For precise detection, tracking, and counting of passengers, while distinguishing them from unrelated objects, the neural networks YOLO [1] and DeepSORT [2] have been employed. Our system is intricately designed to accommodate various passenger categories, including children. Alterations to these networks have been implemented to ensure their accurate functionality in unique public transport settings, such as variable lighting conditions, passengers wearing hoods and outer garments, fluctuating passenger flow densities, and the occasional obstruction by objects.

The primary contribution of this project lies in its comprehensive development and integration of an advanced bus passenger counting system, encompassing the conceptualization, a detailed schematic of interconnected components, algorithmic sequences, and meticulous hardware setup and configuration. The design and execution of controlled experiments, supplemented with video recordings, form the core of this research. Future enhancements will focus on refining the accuracy of head counting, optimizing algorithm updates, adjusting camera viewing angles, and improving overall system performance to ensure more precise and efficient passenger monitoring in public transport settings.

2 Materials and Methods

An innovatively designed passenger counting system, specifically tailored for real-world application in a bus with multiple doors, has been developed. In this custom-built setup, cameras are strategically installed above each door, meticulously positioned to maximize coverage and accuracy. This configuration, developed and tested in an actual three-door bus, represents a pragmatic approach to accurately monitoring and analyzing passenger traffic, demonstrating a commitment to practical, real-world applications in public transport systems.

In the development of the passenger counting system's schema for buses, critical considerations such as accuracy, feasibility of implementation within a bus environment, and cost-effectiveness were meticulously evaluated. The focus was on identifying a solution that achieved an optimal balance between affordability and precision in image processing. This approach ensured the maintenance of a cost-effective system without compromising the accuracy of passenger detection and tracking, thereby establishing it as a viable and efficient option for broad implementation in public transportation systems.

The following components in Figure 1 are required to ensure the operation of video surveillance systems in public transportation:

1. The system is built on a single-board computer that processes video data, interacts with a server for regular information transfer, ensures the compactness and mobility of the system, and supports remote access for updates and enhancements.

2. Video recording and data transmission are realized using USB cameras placed above each door of the bus. The number of cameras depends on the number of doors and allows flexible adaptation to different vehicle types.

3. The direct cable connection between the camera and the single-board computer enables efficient and secure video data transmission without the need for an internet connection. This increases system reliability and security as all data is stored locally in the event of an unstable or intermittent internet connection.

4. The router provides a stable connection by connecting the main computer to the internet via a UTP cable. This connection is necessary for data transfer to the server and system updates.

5. The server receives text information from the main computer for analysis and monitoring. It also receives test video streams and helps in data analysis to improve the accuracy and efficiency of the system. The text data transmitted to the server can subsequently be utilized by other components within the larger electronic ticketing system. This integration allows for a seamless and interconnected operation, enhancing the overall functionality and efficiency of the ticketing infrastructure.

These components form the basis of a reliable public transport video surveillance system, ensuring stable operation with minimal internet traffic costs and providing update and improvement capabilities through remote access.

The strategic positioning of cameras plays a crucial role in the success of an advanced video surveillance system, specifically designed for accurately identifying passengers as they pass through. Choosing the right camera locations is vital, as they need to not only maximize detection precision but also maintain clear visibility under various circumstances.

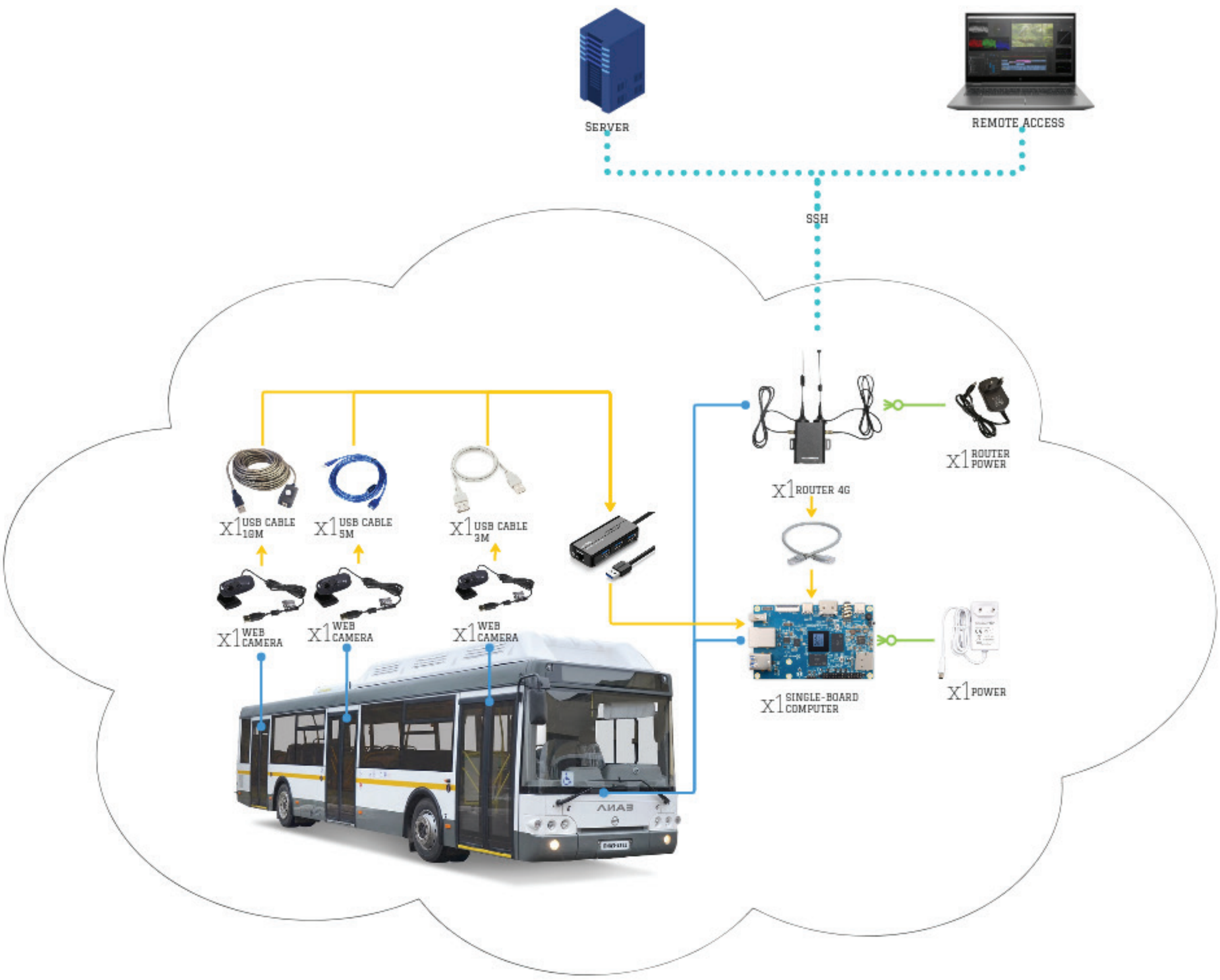

Figure 1 – Components of video surveillance systems in public transportation

To ascertain the most efficient camera placement, several options can be explored. These include positions above the door facing inward, above passengers facing downward, or centrally located in the cabin with a view towards the door. As illustrated in Figure 2, various strategies for camera placement in public transportation are depicted. Each option offers unique benefits for the detection and tracking of passengers. The final selection of the most suitable position should consider a mix of high identification accuracy and the ability to offer an expansive view of the area.

The decision was made to install cameras in the center of the cabin, facing the door, for this project. Positioning cameras above passengers' heads can lead to complications in accurate identification, as temporary identifiers may become mixed up due to movement within the camera frame. However, positioning a camera opposite the door aids in accurately tracking each passenger and reduces the likelihood of incorrect identifier assignment.

During our research, we realized the importance of the viewing angle and camera placement for the accuracy of object detection. Adapting camera settings to specific operating conditions, such as lighting, passenger density, and movement dynamics, can significantly enhance the precision of passenger detection and identification.

Computer vision and machine learning techniques are essential in tracking and identifying passengers within public transport video surveillance systems. Detection, in this scenario, refers to the automatic recognition and localization of objects (such as passengers) within images and video streams. The goal of this detection is to confirm the presence of specific object categories in the visual content and to precisely determine their positions in the frame.

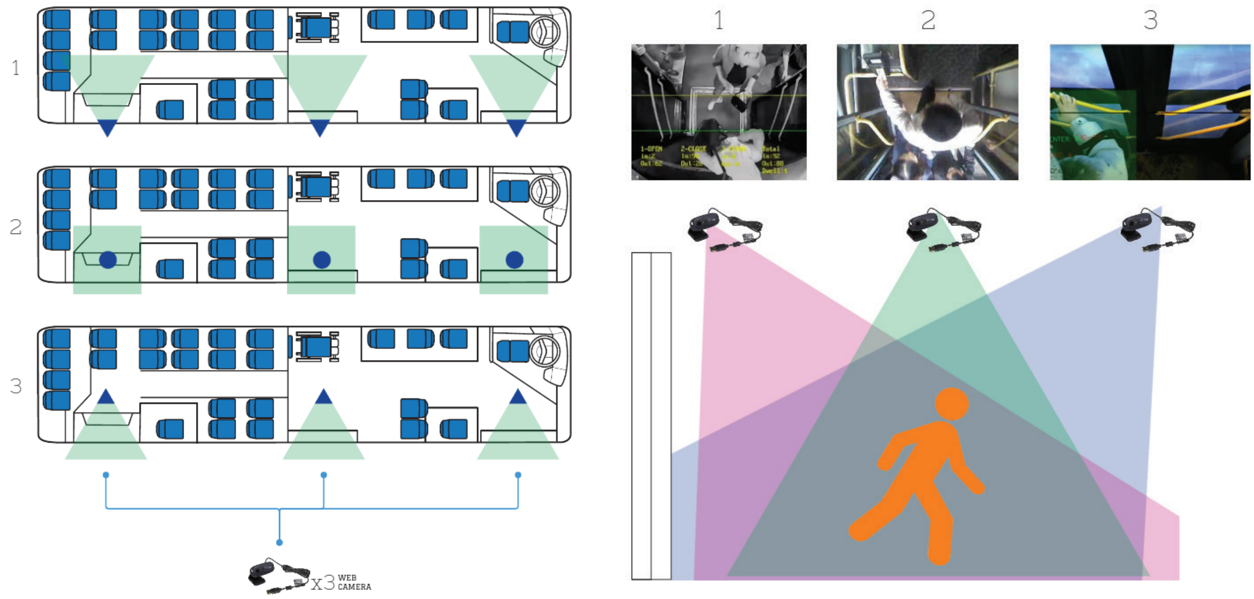

Figure 2 – The surveillance cameras' positions: inside the cabin, downward vertically, and towards the door.

Tracking, conversely, involves the ongoing observation of the movements of identified passengers and the examination of their paths. This function is particularly vital for video surveillance in public transport settings, as it facilitates effective monitoring of passengers in environments that are dynamic and often crowded.

Implemented passenger counting systems in this project employ both detection and tracking data for the accurate enumeration of passengers as they board and disembark the vehicle. By using a defined boarding line within the camera's viewing range, the system is capable of recognizing when a passenger crosses this threshold, thereby appropriately adjusting the total count of passengers in the vehicle.

Figure 3 presents a screenshot from a video capture of a bus traversing routes in Astana city (Kazakhstan), illustrating the functionality of the passenger tracking and counting system. The frame captures a moment where a passenger, assigned ID-9, is crossing the virtual boundary that demarcates the entry and exit zones of the bus. This specific instance, where ID-9 transitions from the 'out' zone (outside the bus) to the 'in' zone (inside the bus) and subsequently exits the camera's field of view, is automatically documented by the system. Consequently, at this juncture, ID-9 is registered by the system as a passenger boarding the bus.

In creating a public transportation video surveillance and object tracking system, significant emphasis was placed on selecting efficient detection algorithms and enhancing the monitoring of passengers. YOLO (You Only Look Once) and DeepSort were chosen for their distinct attributes and effectiveness in handling complex scenes.

YOLO stands out as a cutting-edge object detection method, renowned for its rapid processing and precision. It is capable of identifying objects under various conditions, including different positions, lighting variations, and even when partially obscured. YOLO operates by analyzing the entire image in a single sweep, allowing for swift and real-time detection and categorization of objects. The fifth iteration of this algorithm, YOLOv5 [3-4], was utilized in the project, known for its enhanced accuracy and speed.

YOLOv5 employs convolutional neural networks (CNNs) to extract image features. It segments the image into a grid of cells, determining each cell's bounding box, class probability, and object confidence. YOLO's fundamental mathematical model includes a loss function that mitigates errors in frame positioning, object classification mismatches, and prediction confidence inaccuracies. The model computes the center coordinates, width, and height of each bounding box, adjusting them according to the cell grid size. Therefore, YOLO efficiently minimizes the total loss across all estimated frames, enabling fast and effective object detection.

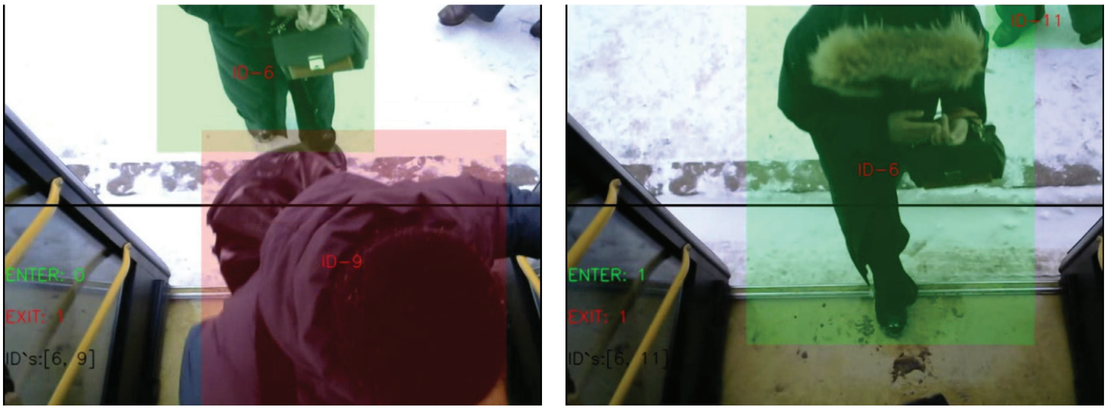

Figure 3 – Screenshots of a video taken inside a bus in Astana city (Kazakhstan)

DeepSort [5-6] tackles occlusion issues in object tracking with a re-identification mechanism, maintaining object identities even when they momentarily leave the field of view. DeepSort integrates deep learning techniques to refine object tracking. Fundamentally, it uses a Kalman filter for predicting object movement and position, and Mahalanobis distance for linking bounding boxes across successive frames. DeepSort mathematically employs the Kalman filter to estimate the state of objects based on previous states and observed measurements, reducing the prediction estimation error. The Mahalanobis distance is calculated for each detection and tracking, facilitating the evaluation of matching likelihood. This algorithm efficiently resolves the challenges of occlusion and proximity by leveraging deep learning to enhance identification accuracy and analyze object features to improve tracking precision.

In the conclusion of this section, a summary of the employed methodologies and procedures is presented:

- The experiment was organized following the schematic depicted in Figure 1. This schema ensures a precise physical and logical architecture of the system, essential for achieving the experimental objectives.

- The overall design of the experiment involves running the program on a single-board computer in debug real-time mode during key times of the day, including peak hours and less busy periods. In debug mode, the program saves frames, thus creating a video sequence that demonstrates the process of passenger counting. Examples of screenshots from this video sequence are presented in Figure 3.

- To verify the accuracy of the algorithm, the number of passengers entering and exiting is manually counted. These data are then compared with the results obtained using the developed algorithm, allowing for an assessment of its efficacy and precision. The calculation of accuracy is detailed in the subsequent chapters.

Figure 4 presents a flowchart describing the operation of the passenger counting system. The source data is a video stream consisting of a sequence of ordered frames. Initially, a function that determines the presence of motion within the frame is activated. If there is no motion, more complex algorithms are not applied. Upon detecting changes in the frame at 5%, equivalent to a change of 10,000-15,000 pixels in a 640×480 resolution frame, the frame is forwarded to the next stage – human recognition using YOLO.

After identifying people in the frame, each detected object is analyzed with DeepSORT. DeepSORT receives the image and coordinates of each detected object, including the top-left corner, width, and height of the bounding box. This facilitates the generation of a feature vector, used for tracking objects across frames. Consequently, DeepSORT assigns a unique ID to each newly detected person, while returning their previous ID to those already registered.

Immediately after assigning IDs, their status is checked: “in” (inside the bus) or “out” (outside the bus). The first status of the ID is determined based on the coordinates, and further status changes are recorded in a dynamic variable reflecting the current state.

Inactive IDs contain valuable information. If ID is absent for 10 frames, its first and last statuses are compared. A status change from “out” to “in” increases the entrance counter by one, and a change from “in” to “out” increases the exit counter. If the status has not changed, the inactive ID is removed from consideration.

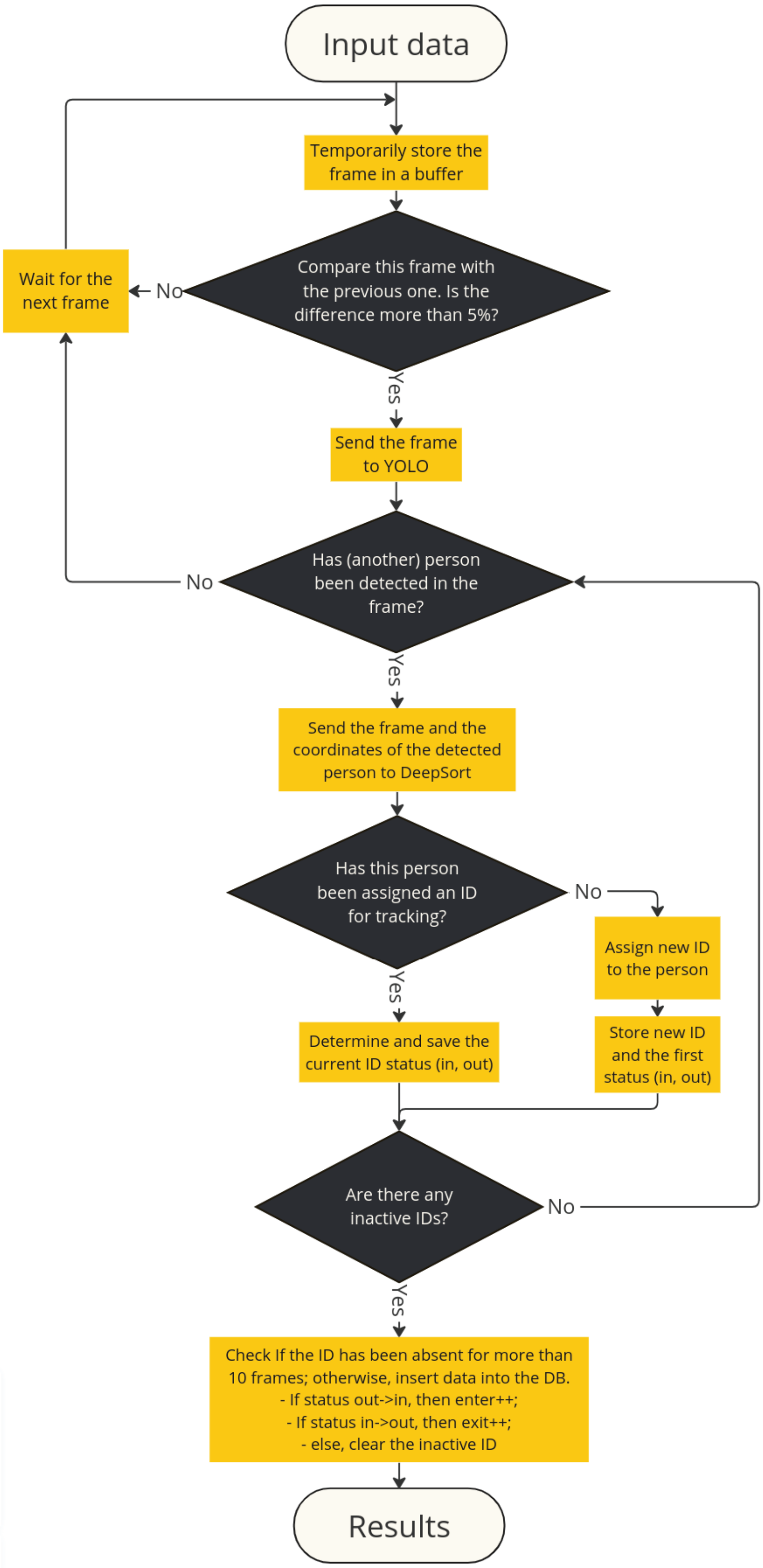

Figure 4 – Flowchart of the passenger counting system

3 Literature review

In contemporary science and engineering, the roles of object detection and tracking are pivotal across numerous applications, including video surveillance, motion analysis, and the enhancement of route networks in public transport. Developing effective algorithms for real-time object detection and tracking is a complex task that requires a comprehensive approach.

Several methods have been explored in the field of object detection, each with its own advantages and disadvantages depending on the application context: NCNN [7] is a lightweight convolutional neural network optimized for mobile devices. Despite their high speed, they are not well suited for tasks requiring high detection accuracy due to their limited accuracy; R-CNN and its derivatives (Fast R-CNN and Faster R-CNN) have shown significant improvements in detection accuracy. However, computational complexity and processing time limit their real-time application; MobileNet SSD [8] offers a good balance between speed and accuracy but its limited input resolution can cause it to miss objects. However, YOLO stands out for its ability to quickly and accurately detect multiple objects in an image simultaneously, making it an ideal candidate for passenger counting systems.

In the field of object tracking, various approaches have also been considered, reflecting the diversity of tasks and application environments: BOOSTING [9] and KCF (Kernelized Correlation Filters) trackers are less tolerant to occlusion and fast motion and are not very effective in crowded scenes; CSRT (Channel and Spatial Reliability Tracker) [10] provides more accurate tracking by taking spatial reliability into account, but increases computational cost; MOSSE (Minimum Output Sum Squared Error) and MedianFlow Tracker focus on fast-tracking but may be less accurate in complex environments; SORT (Simple Online and Realtime Tracking) and DeepSORT combine advanced Kalman filtering and deep learning techniques to improve tracking against occlusion and changes in object appearance; DeepSort can track objects temporarily hidden by other objects while preserving their original identifiers and was therefore chosen for our project.

Analysis of existing research and methods shows that combining YOLO for detection and DeepSORT for tracking is a powerful tool for passenger counting tasks. This approach effectively addresses key challenges such as occlusion, rapid movement, and lighting changes while ensuring accuracy and real-time data processing speed. Future works includes integrating depth sensors to further improve the accuracy and reliability of the system.

These studies are a new approach to passenger counting and introduce a range of methods and technologies, from classical computer algorithms to the integration of the Internet of Things. Many researchers have reduced costs and simplified system implementation by using cameras without depth sensors. Despite the high results, most studies face challenges related to occlusion and changing lighting conditions, and there is interest in further improving the system by integrating additional data such as depth sensors to increase accuracy and reliability.

In recent years, several innovative approaches have been observed in the field of automatic passenger counting in public transportation using various computer vision and machine learning methods: Khan (2020) [11] showed that the accuracy of passenger detection using computer vision can range from 86.24% to 91.2%. Another approach based on the EfficientDet algorithm proposed by Wiboonsiririruk (2023) [12] showed a detection accuracy of up to 94% under different conditions; an approach combining YOLOv2 and MIL trackers proposed by Liu (2020) [13] also showed excellent passenger statistics accuracy, or more, highlighting the effectiveness of synthesizing detection and tracking algorithms.

Many researchers, such as Li's (2017) [14], make use of additional depth sensors such as RGB-D to account for color and depth information, improving the robustness and stability of the method under different lighting conditions and time intervals.

Despite these achievements, most researchers face common problems such as occlusion, variable lighting conditions, and the need to process large amounts of data in real time. Therefore, Nakashima (2019) [15] and Sutopo (2021) [16] suggest the possibility of further improving the system by integrating additional data and adapting algorithms to specific operating conditions.

4 Results and Discussion

At the outset of the study, a series of experiments were undertaken to refine the processing of video data. One such experiment, illustrated in Figure 5, was designed to evaluate the efficacy of utilizing IP cameras in tracking employee movements, specifically their entries and exits within an office setting. During this experiment, it was noted that the employment of IP cameras marginally escalated the video stream processing time relative to alternative approaches. Conversely, the substitution of IP cameras with USB cameras led to a marked decrease in the processing time per frame. This outcome highlights the criticality of selecting optimal equipment to enhance the overall efficiency of the surveillance system.

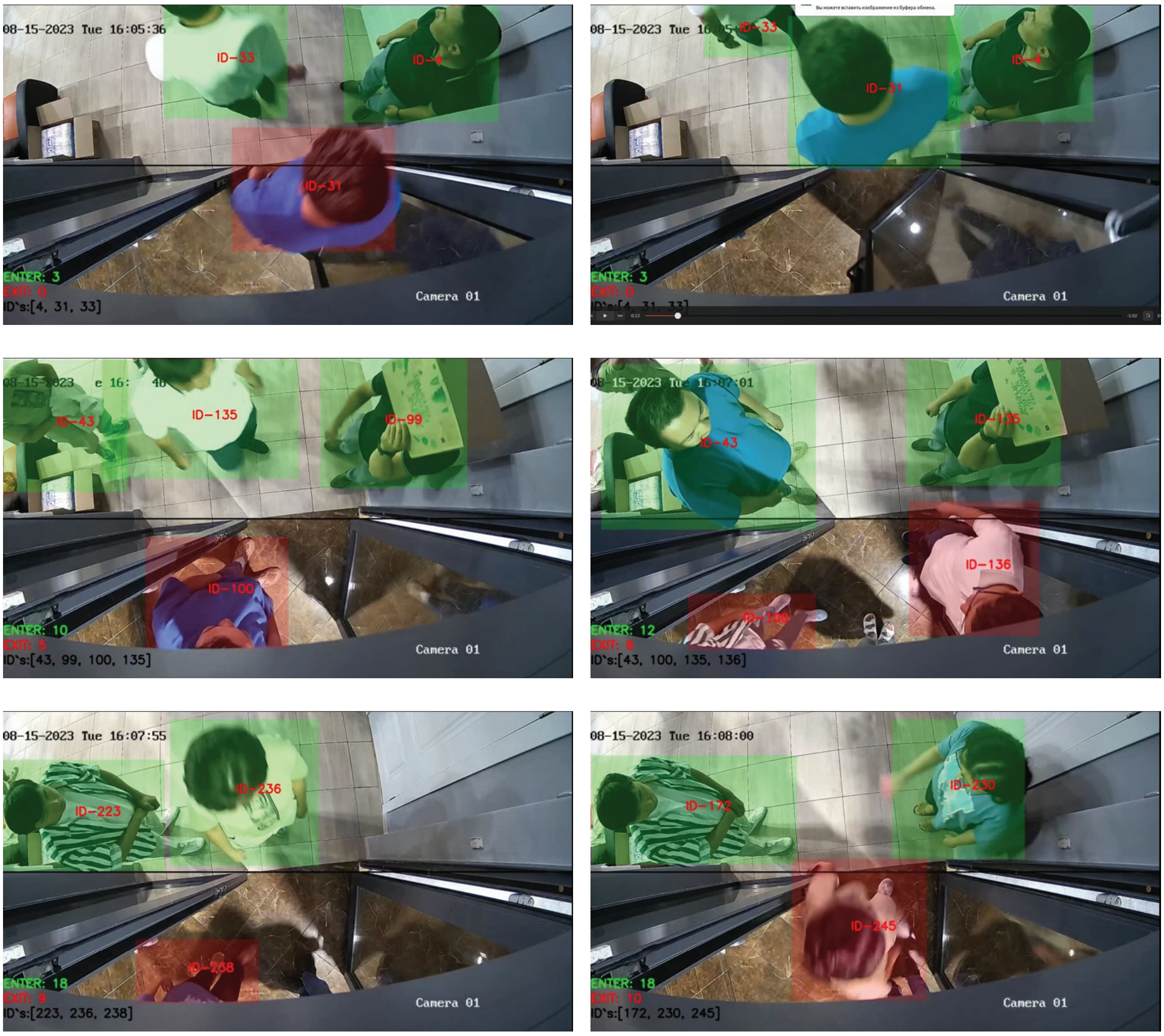

Figure 5 – Screenshots of the video recording in the office

USB camera directly connected to a computer offers immediate access to the video stream via the device driver, facilitating streamlined data acquisition. In contrast, when an IP camera transmits video through RTSP (Real-Time Streaming Protocol), the data traverses the network. This method can result in delays, primarily attributed to network bandwidth constraints. Furthermore, video streams from IP cameras typically utilize compressed formats such as H.264 or H.265. This is in contrast to USB camera streams, which are often transmitted in a format readily amenable to immediate processing. The processing of IP camera streams necessitates decoding, incurring additional computational resources and time.

Practical experience has also underscored the significant influence of camera positioning and viewing angles on the effectiveness of object detection and tracking. As depicted in Figure 6, certain angles can introduce perspective challenges. Objects situated directly beneath the camera are assigned a unique identifier, but as they move, there can be a loss of their original identity due to perspective shifts. This crucial observation played a role in determining a more advantageous camera placement for optimal tracking and identification.

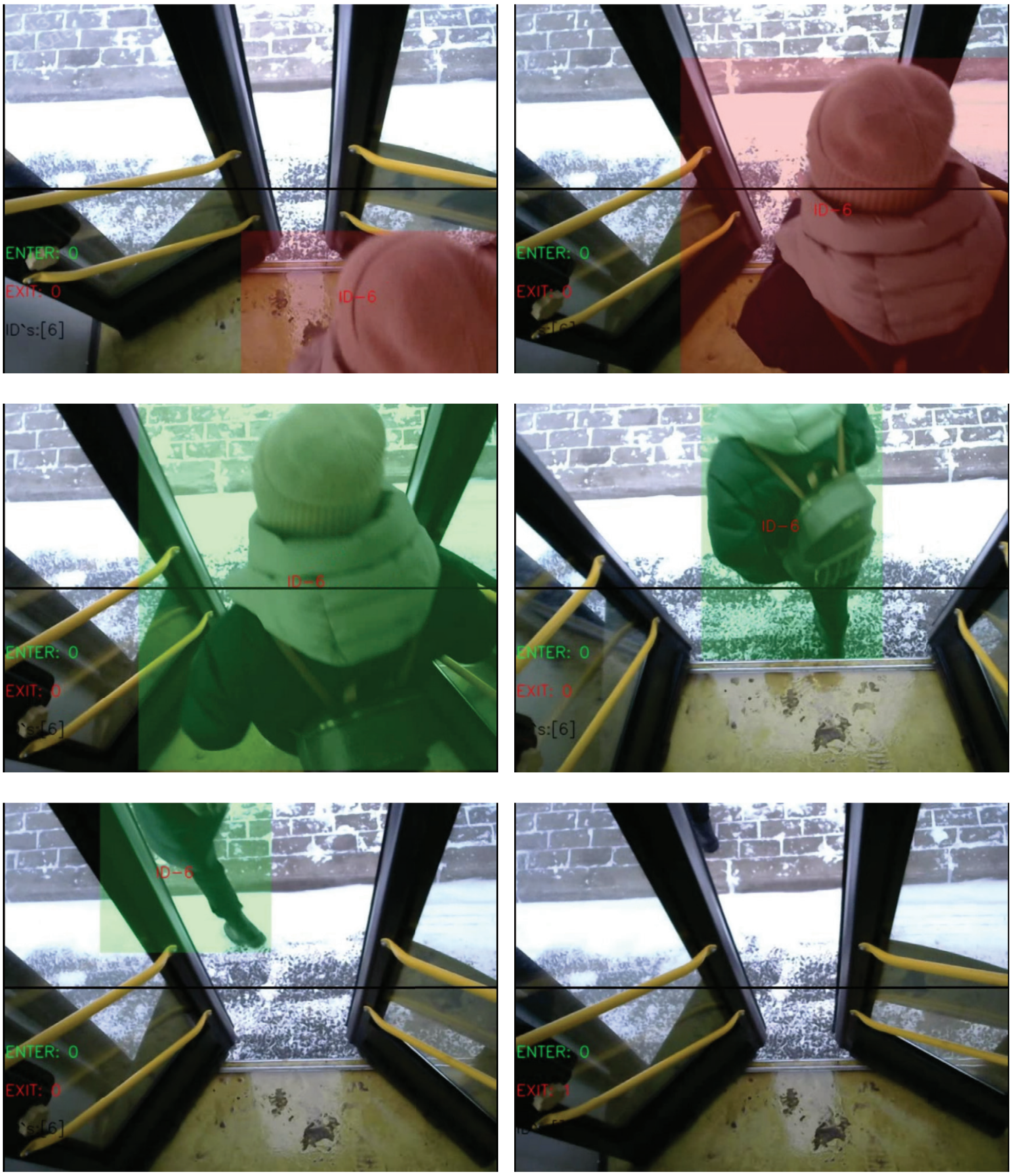

Figure 6 – Screenshots of a video taken inside a bus of Astana

To assess the effectiveness of the surveillance system installed on Astana test buses, a comprehensive approach was applied, focusing on improving the accuracy of data processing. The main criterion of effectiveness was to determine the accuracy of passenger counting using the following standardized performance indicators:

- True Positive (TP) indicates the number of cases where the algorithm correctly classified the passenger actions as boarding or alighting.

- False Positive (FP) indicates the number of actions incorrectly identified by the algorithm as boardings or alightings that did not occur.

- False Negative (FN) record cases where the algorithm failed to recognize actual passenger boardings or alightings.

Used metrics also have a “True Negatives (TN)” indicator. However, this is usually not applicable in such scenarios as it would imply counting people who neither entered nor exited, which is outside the scope.

Based on these parameters, the following key performance indicators of the system were calculated:

- Accuracy reflects the overall proportion of correctly detected actions among all processed cases and is calculated using a formula:

Accuracy = (TP) / (TP + FP + FN).

- Precision is assessed as the proportion of correct identifications among all cases classified as positive by the algorithm and is calculated as follows:

Precision = (TP)/(TP + FP).

- Recall measures the algorithm's ability to detect all true cases among the real passenger behaviors and is defined by the following formula:

Recall = (TP)/(TP+FN).

The testing of current passenger counting systems has yielded informative outcomes, revealing areas where enhancements could be beneficial:

- Accuracy Variations: The tests demonstrated variances in the system's accuracy, precision, and recall, with accuracy peaking at 50%. This indicates a substantial scope for improvement, especially in elevating the system's capability to count passengers more accurately.

- Group Detection Challenge: A principal issue identified is the difficulty in accurately detecting the number of passengers moving in groups when entering or exiting the bus. This highlights the necessity for the development of advanced algorithms specifically designed to handle such complex scenarios.

- Frame Loss Impact: A significant challenge encountered is frame loss during the processing phase, which adversely affects the real-time operation and, consequently, the overall accuracy of the system. The implementation of buffers to manage frame processing has unfortunately led to reduced efficiency and prolonged processing durations.

- Errors with Door Status: The system currently experiences errors particularly when the bus doors are closed, leading to operational malfunctions. The majority of False Negative cases were recorded when the doors were closed, and a person stood near the doors for an extended period, moving from side to side. Therefore, there is a pressing need to devise a mechanism that can accurately detect the status of the bus doors and inhibit system operation during these periods to prevent inaccurate counts.

Table 1 – Real-time video stream processing results on a single-board computer

Device	Input	TP	FP	FN	Accuracy	Precision	Recall
Single-board computer	Real-time	6	4	27	0.160	0.600000	0.18000
Single-board computer	Real-time	12	5	7	0.500	0.700000	0.63000
Single-board computer	Real-time	20	8	18	0.430	0.700000	0.50000

The outcomes of the testing underscore the necessity for additional research and refinement of the passenger counting system. Paramount areas for optimization encompass tailoring the algorithm to proficiently handle scenarios involving automated group passenger counting, diminishing the incidence of frame loss, and enhancing data processing capabilities to guarantee robust performance in real-time applications. A critical factor in this endeavor is the development of mechanisms to precisely ascertain the state of the bus doors, thereby minimizing potential counting inaccuracies. Moreover, determining the most effective frame rate is crucial in striking an equilibrium between processing velocity and recognition precision. Enhancements in these key areas promise to substantially elevate the system's efficacy, transforming it into a dependable instrument for the management of bus passenger dynamics.

5 Conclusion

The development of a video surveillance and passenger tracking system tailored for public transport within this project represents a significant stride in elevating the efficiency of passenger transportation. This achievement is underscored by the meticulous design and implementation of experimental procedures. The project's crowning accomplishment was the construction of an intricate electrical schema and the harmonious fusion of devices, algorithms, and methodologies in an authentic bus setting. Extensive experimentation and video documentation were employed to evaluate the practicality and efficacy of the chosen detection algorithm, YOLO, and the Deep SORT tracking algorithm under real-world conditions. This empirical approach, addressing various challenges such as fluctuating lighting conditions and the need for temporal memory in passenger identification, yielded critical insights.

The experimental framework and the pioneering use of technology within this project are instrumental in establishing the feasibility and transformative impact of the proposed solution on public transportation, enhancing safety, reliability, and operational efficiency.

Looking forward, the project envisions enhancements through incorporating depth sensors and devising new data processing algorithms. The data gathered by the system is anticipated to facilitate the optimization of routes and schedules, thereby rendering passenger transportation more efficient and economically viable.

A particularly salient aspect of this system is its capability to deter fare evasion and elevate passenger satisfaction by offering timely information about traffic congestion. This will not only augment the comfort and convenience of public transportation but also promote more effective resource utilization and the planning of transport services based on actual passenger flow data.

Acknowledgments

We would like to express our sincere gratitude to Innoforce LLP company for their full financial support and for providing the necessary equipment for our project. Their support in implementing the passenger counting system and integrating it into public transportation was invaluable. Special thanks to the Innoforce Team for their professionalism and diligence in establishing secondary connections with bus companies. This collaboration has opened up new horizons for improving public transportation and its efficiency.

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Information about authors:

Rakhymova Aktumar Rakhymkyzy (corresponding author) – Master of Computer Science, lecturer in the Department of Computer Engineering at Astana IT University (Astana, Kazakhstan, e-mail: aktumar@mail.ru).

Mussina Aigerim Bolatovna – Master of Computer Science, lecturer in the Department of Computer Science at al-Farabi Kazakh National University (Almaty, Kazakhstan, e-mail: mussina.aigerim95@gmail.com).

Aubakirov Sanzhar Serikovich – PhD, Associate professor in the Department of Computer Engineering at Astana IT University (Astana, Kazakhstan, e-mail: aubakirov.sanzhar@gmail.com).

Paulo Manuel Trigo Cândido da Silva – PhD, Adjunct professor in the Department of Electronics, Telecommunications and Computer Engineering, Instituto Superior de Engenharia de Lisboa (Lisbon, Portugal, e-mail: paulo.trigo@gmail.com).

Submission received: 07 March, 2024.
Revised: 17 March, 2024.
Accepted: 17 March, 2024.