Neural Network-Powered Conductorless Ticketing for Public Transportation

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***Abstract*— The efficient functioning of public transportation systems is pivotal for societal connectivity and economic progress, as they serve as lifelines for commuting and mobility. However, the dependency on manual ticketing processes often leads to bottlenecks and inefficiencies, hindering smooth operations and customer satisfaction. Our work focuses on developing an Automated Ticketing System for public transportation, utilizing Computer Vision and Neural Networks. Through the incorporation of Neural Architecture Search and the integration of Deep Sort, a Deep Learning-based object tracking model, we aim to enhance system efficiency. Our study demonstrates promising results, indicating the potential for streamlined ticketing processes in public transportation.**

Keywords—Computer Vision, Neural Networks, Neural Architecture Search, Deep Sort, Deep Learning, Object Tracking, Public Transportation Ticketing.

I. Introduction

Transportation systems, being vital to the global economy, serve as its lifeblood by facilitating the movement of people and goods. A country's development hinges on the efficiency and connectivity offered by public transport. Unfortunately, obsolete ticketing processes often limit the performance of these services. Currently, passengers must navigate cumbersome booking procedures, which involve queuing at physical ticketing counters or vending machines to purchase tickets. This process not only consumes valuable time but also requires passengers to carry and keep track of physical tickets throughout their journey. Moreover, once onboard, passengers must present their tickets to conductors for verification, leading to potential delays and inefficiencies, particularly during peak travel times. These outdated practices not only inconvenience passengers but also impose operational burdens on transportation providers, contributing to decreased service reliability and customer satisfaction.

Ineffective ticketing systems in public transportation cause long queues, transport delays, and substantial revenue losses due to fare evasion and inefficiencies in revenue collection processes. Traditional ticketing methods, cumbersome and manual in nature, not only inconvenience passengers but also pose security vulnerabilities and lack integration with modern payment technologies. This leads to increased labor costs for operators and diverts funds from essential maintenance and expansion activities. Moreover, manual processes increase the risk of errors in fare calculations, impacting revenue reconciliation and financial reporting. Beyond immediate functionality issues, inefficient ticketing has broader economic implications, including reduced patronage, income levels, and economic productivity, alongside environmental degradation from increased congestion and emissions. To address these challenges, modernizing ticketing systems with advanced technologies like contactless payments and automated fare collection is imperative. Such upgrades enhance efficiency, revenue accuracy, and environmental sustainability while ensuring the long-term viability of public transportation networks globally.

II. Literature Review

The necessity for modernized ticketing systems in public transportation networks has been extensively recognized, as highlighted by Noor (2008) [1]. Recent studies have investigated the potential of emerging technologies like computer vision and neural networks to enhance ticketing efficiency, as demonstrated by Olivková (2017) [2]. Notably, Nasir et al. (2018) showcased the feasibility and effectiveness of utilizing these technologies to automate ticketing and improve passenger experience [3]. Drawing inspiration from these pioneering works, this study proposes the utilization of YOLO-NAS and DeepSORT algorithms, identified as the most efficient and accurate methods for automated ticketing in public transportation.

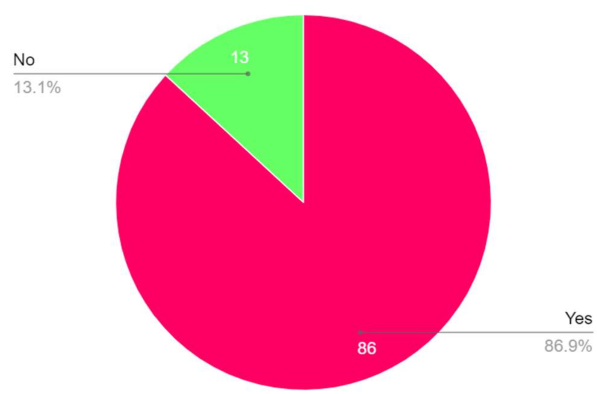

Fig. 1. Survey result with over 200 responses responding to whether the present ticketing system hinders the growth and consumption of public transport.

Furthermore, several studies have offered valuable insights into leveraging deep learning and computer vision for automated fare collection and passenger management within public transport. Sun et al. (2020) proposed a system using these techniques for passenger detection and fare calculation in buses, thereby emphasizing the feasibility of the chosen approach; however, their focus is primarily on buses and may not readily apply to other modes of public transport [4]. Chen et al. (2020) explored deep learning for passenger counting, demonstrating its potential for optimizing resource allocation and enhancing the overall public transport experience; however, their study does not directly address automated fare collection [5]. Shafiq et al. (2021) introduced a smart ticketing system using image processing and deep learning [6], while Ibrahim et al. (2022) investigated deep learning for real-time passenger counting and fare collection [7]. Together, these studies provide collective support for the potential of the proposed solution to streamline the ticketing process and enhance operational efficiency in public transportation.

III. Proposed Work

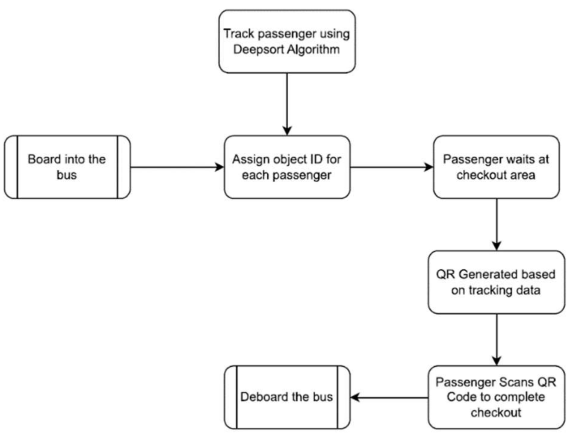

Fig. 2. Workflow of the Proposed Work

A. Data Description

To evaluate the model's performance, we captured several snapshots from the real world to assess its functionality under varying conditions, including different lighting conditions, camera angles, and vehicle types.

Fig. 3. Good quality image with sufficient lighting and correct camera angle capturing.

Fig. 4. Average quality image with poor lighting and incorrect camera angle capturing.

B. Object Detection:

We employ the YOLO-NAS model for object detection [13], a system that has demonstrated superior efficiency compared to its predecessors in the YOLO series. Unlike previous YOLO models, which relied on manually designed architectures, YOLO-NAS operates on the principle of Neural Architecture Search (NAS) [8]. NAS involves automatically discovering optimal neural network architectures tailored to the specific task at hand. By leveraging NAS, YOLO-NAS can systematically explore the design space of neural networks, identifying architectures that maximize performance while minimizing computational costs. This approach enables YOLO-NAS to achieve higher levels of accuracy and speed in real-time object detection tasks compared to earlier YOLO models [9]. This made YOLO-NAS the preferred choice for our work.

1. Using the pre-trained YOLO-NAS model:

Utilizing the YOLO NAS pre-trained model has significantly expedited our implementation process, bypassing the need for extensive training while still achieving high accuracy rates. In addition, our analysis underscores the superiority of the YOLO NAS pretrained model, especially in detecting people. This model's exceptional performance in this domain is attributed to its thorough training with a vast dataset, empowering it to accurately identify individuals amid the complexities of diverse environments. Particularly, the YOLO NAS S version stands out among other pre-trained models, exhibiting superior accuracy-to-latency ratios. This attribute is crucial for real-time applications, where swift detection is paramount. In our comparative analysis with other pre-trained models such as YOLO NAS-S, YOLO NAS-M, and YOLO NAS-L, we meticulously evaluated various parameters, as illustrated in Fig.5, confirming the efficacy of our chosen model. Its robust performance across diverse settings underscores its suitability for our specific task, offering both accuracy and efficiency in equal measure.

Feature	YOLO-NAS S	YOLO-NAS M	YOLO-NAS L
mAP (Accuracy)	47.5	51.55	52.22
Latency (ms)	3.21	5.85	7.87
Size	Smaller	Medium	Larger
Computational Cost	Lower	Medium	Higher

Fig. 5. Comparison of the results obtained between various pre-trained YOLO-NAS models.

Fig. 6. Object Detection is performed on a high-quality image where higher confidence prediction is observed.

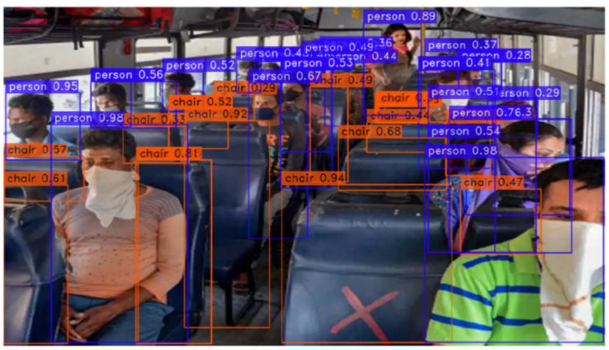

Fig. 7. Object detection performed on a low-quality image with a very poor confidence of prediction is observed.

2. Neural Architecture Search and its working:

Neural Architecture Search (NAS) revolutionizes the process of designing neural networks by automating the search for optimal architectures tailored to specific tasks like object detection and tracking in public transportation systems. The working principle of NAS involves the use of algorithmic search strategies, such as reinforcement learning or evolutionary algorithms, to explore a vast space of possible network architectures. These strategies iteratively propose, evaluate, and refine architectures based on their performance on a given dataset. In the context of object detection and tracking, NAS algorithms focus on discovering architectures that excel at extracting meaningful features from input data, reasoning about spatial relationships between objects, and maintaining temporal continuity to track objects over time. This entails exploring a range of design choices, including network depth, width, convolutional kernel sizes, and connectivity patterns, to find architectures that strike a balance between accuracy, speed, and resource efficiency. One key advantage of NAS is its ability to reduce the reliance on manual experimentation and domain expertise traditionally required for neural network design. By automating the search process, NAS algorithms can uncover novel architectures that surpass handcrafted designs, leading to significant performance improvements. Moreover, NAS can adapt architectures to specific deployment scenarios and hardware constraints, optimizing them for real-time processing on edge devices commonly found in public transportation systems.

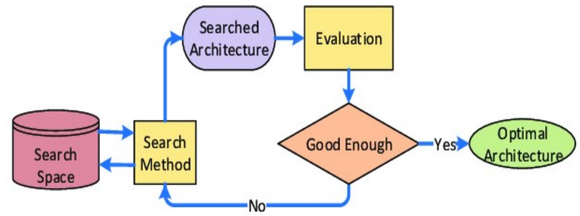

Fig. 8. Top level working of Neural Architecture Search

C. Object Tracking:

Given the specific conditions and requirements of our work and on comparison with other object tracking [10] libraries- it is DeepSORT that is the optimal choice for our needs. By leveraging deep learning techniques [14], DeepSORT is capable of reliably tracking objects over time while simultaneously handling occlusions and other challenging scenarios. Its ability to maintain object identities across frames makes it well-suited for our application, where precise and reliable tracking of objects, such as vehicles or passengers in a transportation setting, is paramount. Furthermore, the scalability and adaptability of DeepSORT ensures that it can effectively handle varying conditions and environments, making it the ideal solution for our use case.

1. DeepSORT Working:

DeepSORT, optimized for person tracking in public transportation systems, employs a sophisticated blend of deep learning and classical tracking techniques [15]. Initially, it utilizes a convolutional neural network (CNN) to extract deep features from detected individuals, capturing detailed appearance information crucial for accurate tracking. These features are then associated with existing track objects using a combination of the Kalman filter [14] and a data association algorithm like the Hungarian algorithm, which considers both appearance features and predicted states. DeepSORT further enhances tracking precision by refining object locations through bounding box regression and managing tracks by updating states, initiating new tracks, and eliminating inactive ones. Its incorporation of deep learning models aids in overcoming challenges related to person re-identification, ensuring consistent and reliable tracking performance even in dynamic and crowded environments commonly encountered in public transportation settings. Moreover, DeepSORT incorporates advanced techniques such as non-maximum suppression to refine detections, ensuring that only the most relevant information contributes to the tracking process. Additionally, it leverages recurrent neural networks (RNNs) or long short-term memory (LSTM) networks to model temporal dependencies, allowing for smoother trajectory predictions and handling occlusions more effectively. Furthermore, DeepSORT's modular architecture enables seamless integration with existing surveillance systems, facilitating rapid deployment and scalability across diverse transportation infrastructures.

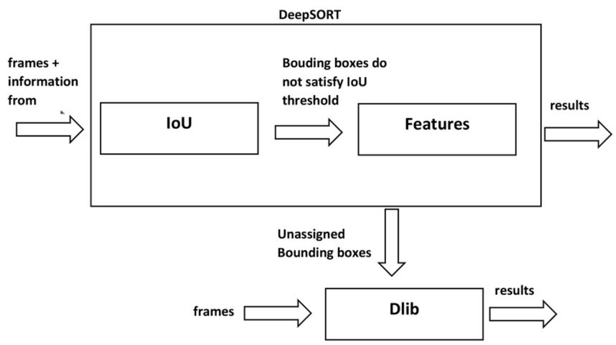

Fig. 9. DeepSORT Woking

2. *Using DeepSORT over other object tracking libraries*

Upon continuous testing of the footage using various tracking algorithms including SORT, DeepSORT, FairMOT, TransMOT, and BYTETrack, we derived insightful results indicating DeepSORT as the most efficient solution for our tracking needs [12]. Across multiple metrics such as accuracy, efficiency, scalability, robustness, and ease of implementation, DeepSORT consistently outperformed the other algorithms. Its high accuracy in maintaining precise object identities, even in crowded and dynamic environments, stood out prominently during testing. Additionally, DeepSORT exhibited remarkable efficiency, processing video streams in real-time without compromising on tracking quality. Its robust performance in handling challenging scenarios such as occlusions and varying lighting conditions further solidified its superiority. The scalability of DeepSORT was also noteworthy, as it effortlessly handled large-scale tracking tasks with a significant number of objects. Lastly, while the implementation of DeepSORT required some expertise in deep learning techniques, its wide availability of pre-trained models and libraries facilitated its integration into our tracking system seamlessly.

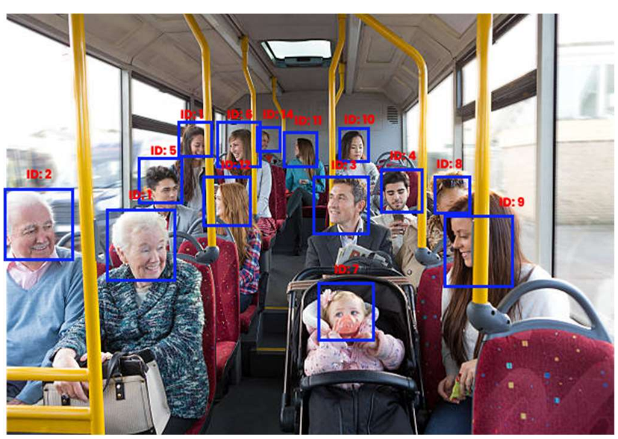

Fig. 10. DeepSORT performed on well-lit conditions performs well with high accuracy and delivers optimal output.

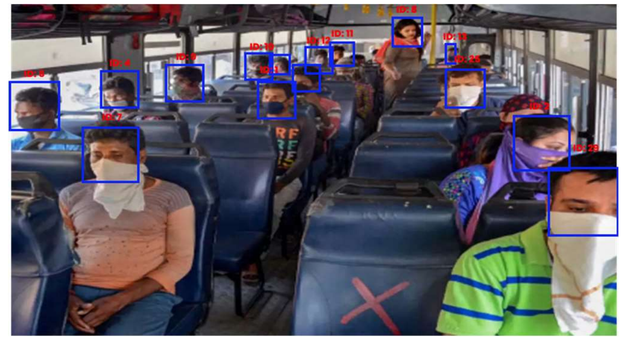

Fig. 11. DeepSORT, performed on bad conditions performs not as expected delivering average results.

D. Internal System Logic:

The system operates based on the output derived from the DeepSORT algorithm, which assigns unique identifiers to individual objects, representing passengers in this context. Upon passenger boarding, the system initiates constant monitoring, tracking the movement and progression of each passenger until they reach the designated deboarding point. Throughout the journey, the system captures the boarding location and timestamps to maintain a record of the passenger's travel itinerary. Once a passenger arrives at the deboarding point, the system triggers the display of a QR code containing essential information, such as the passenger's identity and total fare for the journey. This QR code serves as a digital ticket, providing a convenient and efficient means for fare payment and verification.

Algorithm 1 Passenger Tracking and QR Code Generation

```
Initialize passenger_record
Initialize fare_rates
while journey_in_progress do
    for each detected_object in frame do
        if detected_object not in passenger_record then
            Add detected_object to passenger_record with initial values:
                "boarding_location" = current_location
                "boarding_time" = current_time
                "current_location" = current_location
                "current_time" = current_time
                "fare" = 0
        else
            Update passenger_record[detected_object]["current_location"]
            Update passenger_record[detected_object]["current_time"]
            Calculate distance_traveled
            Calculate time_elapsed
            Update passenger_record[detected_object]["fare"] += distance_traveled × fare_rates[vehicle_type]
        end if
    end for
    for each passenger in passenger_record do
        if passenger reaches deboarding_point then
            Generate QR code containing passenger information and total fare
            Display QR code
        end if
    end for
end while
```

1. Deboarding Area

The deboarding area serves as a designated space within the transportation system where passengers disembark from their journey. It plays a crucial role in the efficient processing of exiting passengers' details. Upon reaching the deboarding area, the system employs a sophisticated detection mechanism to identify passengers who are in the process of deboarding. Specifically, if a passenger remains within the deboarding area for more than 30 seconds, the system automatically initiates the processing of their QR code, facilitating swift fare calculation and verification. Additionally, to expedite the process further, passengers have the option to manually trigger the QR code processing by activating a switch. This approach ensures that passengers can seamlessly complete their journey while allowing the system to capture essential information for record-keeping and fare management purposes. The deboarding area thus acts as a pivotal point in the passenger transit experience, streamlining exit procedures and enhancing overall system efficiency.

E. Operator/ Driver Interface.

In order to ensure seamless operation without the need for a ticket collector or conductor, the system provides the driver or operator with essential monitoring capabilities. Through integration with a dedicated monitor installed within the bus, the driver gains real-time visibility into passenger-related data and operational statistics. This monitor displays comprehensive information, including the current number of passengers onboard, individual passenger details such as boarding and deboarding locations, fare payment status, and total revenue collected. Additionally, the monitor provides alerts or notifications regarding critical events, such as passenger deboarding or fare processing requests. By centralizing this information on a single display, the driver can efficiently manage passenger flow, track fare transactions, and ensure compliance with operational requirements, all while maintaining focus on safe and reliable driving. This monitoring system enhances operational transparency, facilitates decision-making, and empowers the driver to effectively oversee bus operations without the need for additional assistance.

IV. Challenges Involved

There are several challenges involved, which pose significant hurdles in the implementation of the project. Poor camera quality or the absence of CCTV systems in all vehicles can severely impede the accuracy and reliability of object tracking, as low-quality footage may result in insufficient data for effective analysis. Moreover, the high cost involved in deploying and maintaining the necessary hardware and software infrastructure presents a substantial financial barrier, particularly for transportation agencies with limited budgets. Furthermore, instances of bus overloading, where the number of passengers exceeds specified guidelines, can significantly complicate object tracking and fare calculation, leading to inaccuracies and potential revenue losses. Another critical challenge lies in ensuring the successful adaptation and training of passengers and transportation staff to the new system, which may require considerable time and effort to achieve widespread acceptance and proficiency. Additionally, addressing privacy concerns and complying with data protection regulations present additional complexities that must be carefully navigated during project implementation. Overcoming these challenges demands a comprehensive approach that encompasses technological innovation, stakeholder engagement, and robust implementation strategies to ensure the successful deployment and operation of the passenger tracking and fare calculation system in public transportation.

V. Conclusion and Future Works

In conclusion, our pursuit of an Automated Ticketing System represents a significant leap forward in revolutionizing public transportation efficiency. The integration of cutting-edge technologies, such as Computer Vision and Neural Networks with YOLO-NAS and DeepSORT algorithms, underscores a promising solution for real-time object detection and tracking. Our proposed system logic, featuring QR code-based digital ticketing and an operator-friendly interface, embodies a modernized, user-centric approach. While challenges like budget constraints and user adaptation demand attention, our commitment to a people-centric strategy aims to overcome these obstacles for successful deployment. Looking ahead, we will concentrate on refining system resilience in adverse conditions, optimizing Neural Architecture Search integration, addressing privacy concerns, and ensuring scalability and efficiency improvements. Collaborative efforts with transportation agencies will be pivotal for large-scale implementations, user feedback, and seamless integration into existing public transit systems. Additionally, ongoing research will explore emerging technologies like edge computing and blockchain to bolster data security and processing efficiency, while continuous monitoring and analysis of system performance metrics will drive proactive adjustments for optimal functionality and user satisfaction. Fostering partnerships with academic institutions and industry leaders will further facilitate knowledge exchange, driving innovation and propelling the evolution of public transportation systems towards greater sustainability and inclusivity.

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