An Automated Crowd Management in Public Transport Using Online Ticketing System

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Abstract: Due to the rapid increase in population, the usage of public transportation like local buses is increasing day by day, especially in metropolitan cities, particularly in India, one densely populated country in the world. Due to this, we are in need of proper crowd management in public transport, so we have developed automated crowd management in public transport (MTC BUS) through an IR sensor integrated with an online ticket booking system. Due to the unavailability of the estimated time of arrival (ETA) of the bus coming into the bus stop for their destination, a high-demand route is congested with a high number of passengers when compared with a low-demand route at a similar or slight variation of the ETA. This leads to improper usage of public transport and an uneven distribution of crowd density. So, the crowd in the bus is estimated by fitting an IR sensor in the door of the bus for calculating passenger count and classifying them into levels based on crowd density, and the ETA is calculated based on the Machine learning algorithm. Decision-making on allocating bus route numbers is based on ETA and demand for the buses on the selected route. All these processes are connected with the online ticket booking system.

1 INTRODUCTION

Urban bus systems, an essential element of public transportation, face many issues that detract from passenger experience and system efficiency. One of the most critical problems is over passenger crowding, which affects comfort, safety and operational efficiency. First, more crowded buses lead to lower comfortability of passengers and also potential safety concerns (Anju et al., 2022). Crowding obstructs movement, blocks access to exit doors, and raises the odds of accidents or injuries. Second, the long ticket selling time at busy stops greatly delays the bus time. But long queues of passengers result in delayed departures, which in turn reduces efficiency in all parts of the network (Adithi S et al., 2022). Thirdly, increased congestion and inefficient passenger flow due to uncontrolled boarding. No separate queues or entry points, chaotic boarding coupled with the passengers slowing down the crowding process. Next, and more critically, the conventional conductor-heavy ticketing systems, especially in locations with high passenger volume, are detrimental to operational efficiency. Fourthly, boarding patterns are not coordinated (Adline Freeda et al., 2016). Routes are often underutilized, as passengers will board the next available bus. That results in skewed demand across the routes some buses are full while others sit a few seats empty, compounding congestion on certain routes. All of these challenges must be addressed in order to improve the overall service and ridership of bus systems. In this paper, we present a new methodology to address as well as improve the public transport journey for end-users (Ved Prakash Mishra et al., 2019). Hence, ETA refers to the estimated time of arrival of a vehicle to its destination.

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2 RESEARCH OBJECTIVES

2.1 Towards a Dynamic and Efficient Bus System

Build, and train a highly accurate machine learning model to predict bus ETAs for individual routes. Integrate historic data from previous trips with live traffic statistics, and route dependent factors like conditions like weather, and flow of construction. 1- Analyze the data for different aspects and categorize the bus routes into either 1-5 demand levels based on the analysis. In the topical identification phase, relevant data, including passenger volume, peak hour variations, geographical distribution, and others, must be considered (Yu, B., Yang, Z., Yao, J., 2010). Implement an algorithm that is capable of providing real-time recommendations on the best routes to take for passengers. Use predicted ETAs, route demand categories, and, if available, passenger preferences, as well as live bus locations. Optimize passenger wait times and throughput by favoring routes with less demand and lower ETAs Create a display for passengers and onboard buses at bus stops that shows this information to promote transparency and informed decision making when planning travel (S. Rajaprakash et al., 2020).

3 RELATED WORK

3.1 Machine Learning for ETA Prediction

Deep learning models like LSTMs have shown promise in predicting passenger boarding/exiting patterns and improving ETA accuracy (Gandhi et al., 2023). Ensemble methods combining different models like Random Forests and SVMs can further enhance accuracy (Liu, R., Li, S., Sun, L., Li, F., & Sun, Z. 2017).

3.2 Demand-Based Route Allocation

Dynamic optimization algorithms considering real-time demand and bus locations have achieved significant reductions in passenger waiting times (Zhang et al., 2021). Decentralized multi-agent systems offer flexible route assignment based on local information.

3.3 Crowd Density Sensing

Infrared sensors provide accurate passenger count data within buses (S. Muthuselvan et al., 2015). Computer vision algorithms using cameras can estimate crowd density and passenger behavior for real-time monitoring (Patil, S. A., and Soman, S. S. 2017).

4 METHODOLOGY

4.1 Data Collection and Processing

Historical Data: Collect historical data on bus speed, distance, and Estimated Time of Arrival (ETA) for various routes (Correia et al., 2014). Pre-process the data to ensure its quality and consistency. Real-Time Data: Implement a system to gather real- time speed data using GPS sensors on buses. Integrate infrared (IR) sensors at bus stops to count passengers entering and exiting. Store the real-time speed and passenger count data in a Firebase Real-time Database for immediate access.

4.2 Machine Learning Model for ETA Prediction

Train a machine learning model on historical data to predict bus arrival ETAs based on real-time speed information. Utilize simulated speed data during the training process to mimic real-life GPS data behavior (Meghana Sarode et al., 2020). Deploy the trained model to continuously generate predicted ETAs for each bus stop and update them in the Firebase database.

4.3 Demand Category Classification

Define a Demand Category classification system for routes based on the following:

Sequence of Bus Stops: Analyze the sequence of total bus stops before the source stop and the overall sequence within the route. Higher sequence numbers indicate potentially higher passenger volumes. Assign lower Demand Category values (e.g., Category 1) to routes with lower passenger volumes and higher values (e.g., Category 5) to routes with higher volumes.

4.4 Route Allocation Algorithm

- Develop an algorithm that considers the following parameters when allocating routes to buses:
- Demand Category: Prioritize routes with lower Demand Category values to minimize passenger crowding.
- Predicted ETA Difference: If multiple routes have the same Demand Category, compare predicted ETAs at the source stop (Mr. Kruthik Gandhi H A et al., 2023).
- Select a route with a predicted ETA difference below a pre-defined threshold (e.g., 5-10 minutes) from the average predicted ETA.
- Passenger Count: If there is a tie between the demand category then use this passenger count crowd level to decide if the best route exists or there are no significant ETA differences, consult the real-time passenger count data.
- Allocate the route with a passenger count below a specific threshold to distribute passenger load across routes.

```
String crowd Level = "";
if (count >= 1 && count <= 10)
{
        crowdLevel = "Seats Available";
}
else if (count >= 11 && count <= 20)
{
        crowdLevel = "Less Crowded";
}
else if (count >= 21 && count<= 30)
{
        crowdLevel = "Crowded";
}
else if (count >= 31 && count <= 40)
{
        crowdLevel = "Highly Crowded";
}
else
{
        crowdLevel = "Highly Dense
Crowded";
}
```

4.5 System Implementation

Integrate the data collection modules (GPS and IR sensors) and the route allocation algorithm into a central system using a Raspberry Pi Pico W or similar microcomputer. Utilize the Firebase Real-time Database to store and access the collected and predicted data for real-time decision-making.

4.6 Evaluation and Testing

Evaluate the effectiveness of the system by comparing passenger wait times, overcrowding levels, and overall system efficiency before and after implementation (Sri Sindhuja Selvanayaki P et al., 2018). Conduct simulations and field tests to validate the accuracy of the ETA prediction model and the overall functionality of the route allocation algorithm.

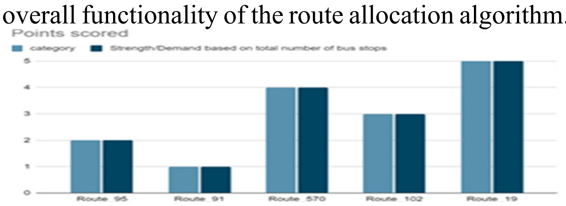

Figure 1: Points Scored by the Different Bus Routes.

To achieve highly accurate passenger inflow and outflow data, we propose a multi-sensor approach at each bus door's entry/exit points. Infrared (IR) sensors will be strategically positioned to ensure unobstructed views and protection from potential damage or external interference. Additionally, by employing more than one or two sensors in a combined configuration, we can significantly enhance passenger detection accuracy. Figure 1 shows that the points scored by the different routes. This redundancy will mitigate the limitations of individual sensors and account for potential occlusions caused by luggage, backpacks, or closely following passengers. Data Collection: Continuously collect real-time passenger count data from each sensor and update under each route and bus stops in firebase real time database, ensuring data points are time stamped for accurate timing and synchronization. Implement data quality checks to identify and handle potential anomalies or sensor malfunctions.

Algorithm for Crowd Level Classification: Establish data-driven passenger count thresholds for each crowd level, considering: Average passenger capacity of buses in your system. Comfort and safety considerations for passengers. Potential variations in passenger size (e.g., luggage, standing vs. seated)

4.7 Widget for Ticket Booking App

Displaying the assigned route ID, predicted ETA, and crowd level information (e.g., "Level 3: Crowded") in a widget within the ticket booking app. This information helps passengers make informed decisions about route selection and travel time.

4.8 E-Ticketing and Passenger Flow Data Collection

To expedite boarding and gather accurate passenger data, we will utilize e-tickets displayed on smartphones or electronic devices. These e-tickets will showcase a scannable barcode (e.g., QR code), a clear Ticket ID, and validity information. Passengers will present e-tickets for scanning or visual verification at entry points. Validated tickets grant access, while invalid one's trigger alerts. The e-ticketing system automatically captures passenger ID, boarding time, and entry point for analysis and route optimization. This system can be integrated with the IR sensor-based passenger counting system to enhance accuracy, validate data, and generate comprehensive passenger flow reports. The below table 1 and table 2 shows that the SRT Tools and Tidel Park stoppings respectively.

5 RESULTS AND DISCUSSION

Table 1: Route Details with Their ETA for Tidel Park Stopping.

Serial No	Route ID	Bus Stop	ETA
0	95	Tidel Park	7 minutes
1	91	Tidel Park	9 minutes

Table 2: Route Details with Their ETA for SRP Tools Stopping.

Serial No	Route ID	Bus Stop	ETA
0	102	S.R.P.Tools	12 minutes
1	570	S.R.P.Tools	10 minutes
2	19	S.R.P.Tools	14 minutes
3	95	S.R.P.Tools	9 minutes

Logic simulation of minimum ETA if the selected source has more than one entry with ETA than give least ETA routes id information and if there is tie or it mean equal ETA in the database than return the routeid information based on least value of category entry among five routes collection than return than only routeid information field in database if the selected source has only one (Sharma D. et al.,2016).

The below figure 2 shows that the journey ticket booking in public transport.

Figure 2: Journey Ticket Booking in Public Transport.

Decision making of allocating route id for same ETA for same source on different route id

Example 1:

Source = S.R.P.Tool, ETA"6"

category"1"

source"S.R.P.Tool" route 91 and another ETA"6"

category"2"

source "S.R.P.Tool" rout95

In this same ETA which the allocation is based on category which has least value as per logic it is routeid91 has 1 which is least

Decision making of allocating route id for difference in wide range of ETA for same source on different route id

Example 2:

Source ="Kandhanchavadi" ETA"11"

Category"2" 95 routeid

source"Kandhanchavadi"

And another ETA"8"

Category"1" 91 routeid

source "Kandhanchavadi" and another ETA"58" Category"4" 570 routeid

source "Kandhanchavadi"

The allocation of route id is 91 which has least ETA 3. Decision making of allocating route id for selected source has only has single routeid

Example 3:

```
source=parrys ETA"1"
        category "5"102 routeid
source "Parrys" allocated route id is
102
```

The output of widget displaying ETA, Route ID, Crowd Level shows in the figure 3

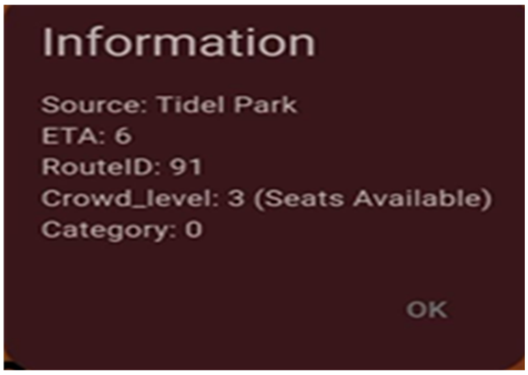

Figure 3: Output for Identification of Crowd Level.

The E_Ticket Display with Ticket ID and Barcode is shown in this figure 4.

Figure 4: E_Ticket Display with Ticket ID and Barcode.

Accurately classifying crowd density with sensor data demands meticulous attention to detail. The type and placement of sensors play a crucial role, with bi-directional infrared detectors strategically positioned at entry/exit points offering reliable passenger count data. Robust algorithms trained on diverse datasets further enhance accuracy and adaptability. Studies showcase promising results, with some exceeding 90% accuracy in real-time estimation using sensors and computer vision. Figure 5 gives the device activation image.

Nonetheless, there are limitations that must be addressed. Sensor readings can also suffer from noise due to passenger behaviors, luggage sizes, and movement patterns (D. Darsena et al., 2017). Downtime due to external factors that can hinder the sensor or disrupt data interpretation like obstacles, lighting and environmental noise.

Figure 5: Device Activation.

The sensor data mainly shows the number of passengers in the bus, but lacks information on their behavior (standing vs. sitting). Additionally, inaccurate classifications can result for certain demographics or scenarios due to biases in training data or algorithm design.

Nonetheless, it is important to note that sensor-based crowd density classification could still be extremely valuable if tailored intelligently (Lavanya S et al., 2017). Following proper sensor selection and arrangement, using powerful algorithms trained on abundant and diverse data, and doing everything to take into main consideration the impact of external factors and limitations, this can turn out to be a strong tool to manage public spaces and maximize efficiency.

6 CONCLUSIONS

Increased convenience and reduced frustration: Improved bus arrival time estimates (ETAs) allow better planning and reducing waiting times at bus stops, creating a better and more predictable travel experience. Greater comfort and safety: details of crowd numbers in real time allow passengers to board less crowded buses, improving comfort and reducing the risk of safety. Informed travel decisions: Access to ETA, demand and crowd data allows passengers to make decisions on which bus to take or a different mobility option, optimizing their journey. Balanced system and reduced overcrowding: Allocating routes according to demand categories (1-5) can lead to a more balanced system with passenger supply matching routes capacity to improve efficiency and reduce crowding. IR sensor-based passenger counting system is assisted with to improve the accuracy of the system.

Optimized route-planning– Through real-time data, operators can understand demand per route, thus deploying buses themselves and efficiently optimizing operational costs, as well as reducing congestion. Better resource utilization: Real-time passenger volume data allow operators to deploy only those buses that are in demand, preventing empty or overcrowded vehicles and effective resource utilization.

Utilizing historical data and real-time data analysis for strategic decisions (route expansion, fare changes, and even improving infrastructure) promotes a data-driven decision-making method of public transportation management.

6.1 Additional Potential Results

Environmental benefits: Optimization of routes and reduction of congestion can result in reduced fuel consumption and lower emissions, therefore leading to a cleaner environment. More members on the bus: A more reliable, comfortable, data-driven bus can win over newcomers, and encourage existing riders to ride more often, promoting sustainable transport choices. Increase the public perception: the machine-centric system which utilize real-time information to improve travel experience can enhance public's view about public transportation, provoking its more extensive use.

6.2 Limitations

Although our selected model showed promising results in predicting ETA (bus arrival time), we believe there can be a better approach. Advancing to more complex Models such as XGBoost or design specialized Sequential models such as LSTMs, & Extending the Data Set further back in time to include weather patterns & special events are a few of the ways in which we could hone in more accuracy and address for corner cases. And while bi-directional infrared sensors are good for reliable passenger counts, they also have limitations such as possible interference and lack of information about individual behavior. Exploring other technologies, such as computer vision with depth cameras or radar sensors, may help create more complex datasets and help with more nuanced crowd characterization, such as separating standing from seated passengers. Such deeper insights can facilitate dynamic capacity modifications and further ensure enhanced resource allocation. Our ongoing efforts towards increasing the accuracy of our model and the most insightful ways of data collection we can achieve will allow us to further optimize the performance of our system so we can provide an even more time- effective and comfortable experience for end users and public transport operators.

6.3 Future Work

Our work highlights the promise of real-time data and automated systems in improving public transportation experiences. However, continuous development is crucial to maximize its impact. Here are key areas for future exploration

6.4 Enhanced ETA Prediction

Advanced Models: Consider the benefits of integrating XGBoost, LSTMs, or ensemble approaches to provide a more resistant and precise arrival time forecast, accommodating unusual cases and intricate circumstances. Grow Data Sources: Introduce more periods including climatic patterns, exceptional events and real-time traffic conditions to supply a fuller picture about possible delays in a specific area make model further adaptability. Hyper parameter tuning: Once the model has been chosen, hyper parameters for the model should be optimized and updated over time to maximize performance against particular conditions within your system.

6.5 Advanced Crowd Characterization

More than a head count: They also can go beyond just counting passengers by using alternative technology, such as computer vision coupled with depth cameras or radar sensors. This would help collect richer data sets in terms of enhanced crowd characterization, for example passenger movement patterns, real-time availability of seats and even standing vs seated passengers. Granular insight: Use these richer data sets to develop a better understanding of crowd behaviour in buses. This data could also be leveraged to enable dynamic adjustment with respect to capacity, where resources are targeted toward specific areas or passengers are informed via mobile how to avoid congestion and utilize alternate routes for a smoother journey.

By tackling these constraints and following up on these exciting future directions, we can further improve and advance our proposed system. This will ultimately lead to a more efficient, reliable, comfortable public transportation experience for all.

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