Accurate People Counting Model for Smart Mobility using WiFi Channel State Information

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***Abstract*—In recent years, the advent of wireless communication technologies has revolutionized the transportation industry, enabling the development of smart transportation systems. One such technology that has gained significant attention is Channel State Information (CSI). Effective monitoring of users in these transportation systems is essential for optimizing operations and ensuring passenger safety and satisfaction.**
Therefore, this paper presents a novel approach to estimating urban mobility through a People Counting Long Short-Term Memory (PC-LSTM) model. Utilizing WiFi CSI, the PC-LSTM method accurately counts the number of passengers in public transport vehicles without compromising privacy. The model outperforms existing methods with an impressive mean accuracy rate of 99.44% across various scenarios, offering a reliable and privacy-preserving solution for smart city infrastructure. This research contributes significantly to the advancement of sustainable urban mobility systems.

***Index Terms*—Crowd Monitoring, WiFi Network, Deep Learning, Public Transport, Automatic Passenger Count.**

I. Introduction

Rents and house prices in Europe are constantly rising. In the third quarter of 2023, house prices and rents in the EU increased by 0.8% compared to the second quarter of 2023[1]. As a result, many European citizens tend to move from more expensive cities to nearby centers, sometimes increasing the distance between home and work and forcing people to make long journeys by car or public transport. To accommodate this growing demand, cities must offer their citizens an excellent public transport service (PTS) commensurate with the number of passengers requiring the service. Transport routes must be planned, vehicle capacities must be adapted, and ticketing services must be efficient and usable. Among the above-mentioned transport requirements, the vehicle's capacity is of extreme importance because an incorrect underestimation of the flow of people can lead to overcrowding and will prevent some passengers from using the service. This challenge has driven significant research in crowd monitoring and people counting, leading to technological advancements aimed at improving transport efficiency. A clear example is the role of wireless technologies in transforming the transportation industry. In recent years, these innovations have enabled the development of smart transportation systems, demonstrating the growing intersection of IT research and urban mobility solutions [1]. These systems leverage wireless connectivity to enhance efficiency, safety, and the overall passenger experience.

One of the most promising technologies for passenger monitoring is Channel State Information (CSI) [2]. CSI refers to the information obtained by a wireless device regarding the characteristics of the communication channel, including both amplitude and phase data. Since human presence, movements, and even biological signals (e.g., breathing and heart rate) affect CSI amplitude variations and phase shifts, this information can be leveraged for a wide range of applications, including gesture recognition [3], crowd counting [4], [5], and respiration detections [6].

Using CSI in WiFi-based people detection and counting offers a significant advantage: it enables device-free approaches, meaning that individuals do not need to carry electronic devices for detection. Instead, CSI-based methods analyze wireless signal disturbances to estimate the number of people in a given area. This approach ensures privacy, ease of deployment, and cost-effectiveness, making it a compelling alternative to camera-based systems.

Therefore, in this paper, we introduce our People Counting Long Short-Term Memory (PC-LSTM), adopting a straightforward methodology to analyze WiFi CSI data. These steps are necessary to transform the data into a sequential format suitable for learning processes performed by the PC-LSTM. For training our neural network and providing comparable results, we have considered the open datasets EHUCOUNT [7]. We have evaluated the performance of the proposed PC-LSTM model in terms of accuracy across different scenarios. To provide a basis for comparison, we have also presented the results obtained by other approaches. Our proposed PC-LSTM model outperforms previous state-of-the-art methodologies, which demonstrates its effectiveness as a reliable method that a PTS can use onboard its vehicles. The provided contributions are as follows:

- a methodology that allows the PTS to count the exact number of people inside a vehicle without requiring any action from the user or the use of a mobile application on the user's smartphone is proposed;
- a Long Short-Term Memory (LSTM) model that accurately estimates the number of people inside PTS

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[1]https://ec.europa.eu/eurostat/web/products-eurostat-news/w/ddn-20240110-2#

vehicles while ensuring user privacy is developed. Unlike camera-based counting systems, our system uses WiFi CSI amplitude and phase data analysis, which does not collect any personal information from users. This enables the PTS to avoid complying with regulations related to the management of personal data.

The structure of the paper is as follows: section II examines the background on people monitoring in indoor scenarios and inside vehicles, section III contextualizes the scenario and describes the proposed PC-LSTM solution, section IV describes the public dataset used for the evaluation of the algorithm, V analyzes the obtained results, comparing them with the State-of-the-Art, and finally the VI concludes the paper.

II. Background

Over the years, the PTSs have tried different ways to estimate vehicle occupancy in real-time. The authors of [8] have developed an automatic passenger count (APC) system for transit vehicles using existing surveillance cameras. They employed the YOLOv8 algorithm for object detection and combined it with the deepSORT tracking algorithm. However, the use of cameras for surveillance raises privacy concerns, as they capture frames with people's faces.

Infrared sensors may be a possible solution to overcome the cameras' privacy issues. The infrared sensor can create an image without the details given by common cameras, reducing the possibility of recognizing individuals from images. To understand the efficiency of this technology in an APC system, the authors in [9] compared the accuracy and complexity of various object detection, point-level localization, and image-level counting models, including YoloV8 and DINO for object detection, P2PNet and PET for point-level localization, and ConvNeXt and ViT for image-level counting. The study indicates that models with image-level annotation can achieve competitive accuracy with a higher frame rate and similar model parameters compared to more complex YOLO detectors and point-level localization models. It is important to note that a subject close to infrared sensors may allow the sensor to capture his facial characteristics, making him recognizable to third parties if recorded.

The Internet of Things (IoT) has significantly contributed to the advancement of APC Systems in observing urban mobility. The adoption of APC systems has been led especially by the emergence of portable and mobile devices such as smartphones and smartwatches. These devices provide new opportunities to collect detailed passenger data and track their movements throughout cities. The paper [10] discusses a novel lightweight convolutional neural network (CNN) model for people counting using Ultra-wideband (UWB) impulse radar in IoT applications demonstrating an impressive 99.38% accuracy score and maintaining it even after quantization, with fast inference times on STM32 microcontrollers.

In their work [11], the authors aimed to detect the probe requests sent by WiFi-enabled devices during active scanning. This approach allowed them to count the number of people present in a particular area, and analyze their patterns of permanence and return. The authors put forward a new de-randomization technique to overcome the MAC address randomization process implemented by manufacturers to safeguard the user's privacy. Still regarding the WiFi packets sniffing approach, in work [12], the authors focus on MAC de-randomization, orienting its application to a simulated bus environment, demonstrating the possibility of using this APC approach in a PTS environment.

However, there are other ways to adopt WiFi technology besides just sniffing its packets out. For this purpose, the study of signal disturbance using Channel State Information (CSI) analysis of the WiFi can highlight how a person can interfere in the transmission of the WiFi signal and, from this, understand how many people interfere with the WiFi signal. In the study [4], a CSI-based approach was proposed to estimate the number of people in a room. The authors analyzed various features related to the dynamic state (moving crowd) and static state (location of the crowd) from the CSI bundles. Finally, they used these features to train machine learning (ML) and deep learning (DL) models. However, the approach remains incomparable since the authors did not release the dataset or the estimation models.

In [13], the deployed system is an effective real-time Passenger Counting (Pa-Count) method that can be applied to moving vehicles. It has been tested in both a car and a subway carriage. The main idea revolves around detecting passengers' fidgeting, which induces signal fluctuations that affect CSI measurements. The authors set a pair of antennas to create a Fresnel zone, detecting fidgeting events through a Fresnel zone model. Variations in CSI signal amplitude caused by fidgeting are analyzed to identify these events. Once detected, the signals are mapped to passenger numbers, establishing a counting model based on fidgeting distribution and queuing theory. The system leverages a maximum a posteriori (MAP) estimation approach to correlate passenger fidgeting with the total passenger count. The overall accuracy in this case is of 93.75% counting 5 people inside a car and of 92.60% in the subway when the number of passengers is less than 16.

These studies demonstrate the potential of WiFi CSI-based passenger counting as a privacy-preserving and ease of deployment alternative for public transport occupancy estimation.

III. System Model

A. Reference Scenario

Figure 1 illustrates the reference scenario considered in this study.

The physical layer can consider indoor and outdoor scenarios, i.e. train and bus/tram vehicles, railways and metro stations, and bus/tram stops. In this first approach, the environment represents a public transport vehicle, such as a bus, a train carriage, or a metro car. In this scenario, two devices are strategically positioned to establish a continuous wireless communication link: one functioning as the transmitter (TX) and the other as the receiver (RX). Wireless communication

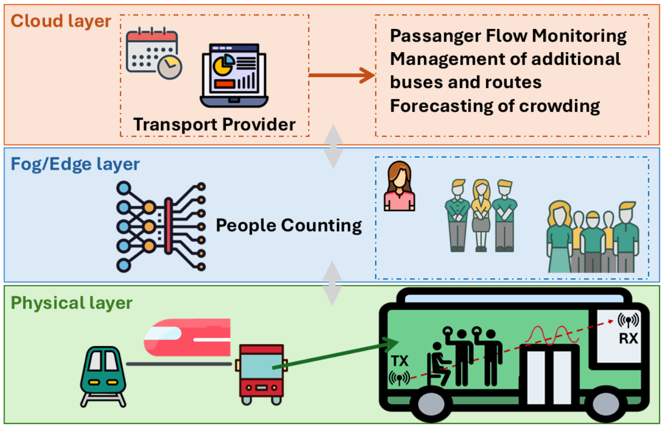


Fig. 1: Reference Scenario of the Proposed System

is maintained through technologies such as WiFi, enabling the collection of CSI data.

Inside the vehicle, passengers may move freely, remain standing, or take a seat. The CSI data collection process is carried out using devices equipped with network interface cards (NICs) and specialized tools tailored to the hardware specifications, allowing the system to capture, store, and analyze the received data. The collected CSI data provide insights into how variations in passenger numbers influence signal propagation by altering the physical characteristics of the communication channel.

Factors such as individuals' presence or absence, movement, and speed induce fluctuations in the CSI across both time and frequency domains. These variations can be leveraged to estimate the number of occupants inside the monitored area using ML techniques capable of learning from past data and recognizing patterns that can be used to infer the number of passengers. To enable this process, the vehicle is equipped with a WiFi access point and a WiFi receiver capable of extracting the corresponding CSI data. The employed devices can vary in type, including simple, low-cost, and non-intrusive hardware solutions such as ESP32 modules or Raspberry Pi boards with appropriate communication interfaces. The receiver node collects the CSI data and forwards them to upper layers, such as Fog, Edge, or Cloud computing layers, for further processing.

At the Fog/Edge layer, the CSI values undergo preprocessing and noise reduction before being analyzed using the PC-LSTM algorithm. This algorithm is designed to automatically estimate the number of occupants within the vehicle by identifying patterns in the received CSI data. The primary objective of this system level is to learn different occupancy patterns and subsequently predict the number of passengers inside the vehicle based on real-time CSI readings.

By leveraging occupancy data and monitoring crowd density across the fleet, transport service providers can develop advanced crowd management functionalities. These functionalities enable intelligent and proactive passenger flow control, helping to mitigate overcrowding and improve overall transport efficiency.

B. PC-LSTM Algorithm

The approach used to estimate the number of passengers within the transport system relies on a specialized type of neural network known as a Long Short-Term Memory (LSTM) network [14]. LSTM networks differ from traditional Recurrent Neural Networks (RNNs) because they are specifically designed to capture short-term fluctuations and long-term dependencies within time-series data. While in standard RNNs, the output is influenced by both the current input and the system's previous state, in LSTMs, memory cells are introduced that significantly improve the ability to preserve crucial information over prolonged periods.

A typical neural network structure comprises three main components: an input layer, responsible for receiving data; multiple hidden layers, where computations occur; and an output layer, which generates the final predictions. Within the hidden layers, the network consists of interconnected units, each associated with trainable weights (w) that are optimized during the learning process. These weights determine how much influence each unit has on the final prediction, allowing the model to adjust its internal parameters based on training data that maps inputs to expected outputs.

In IEEE 802.11, the orthogonal frequency-division multiplexing (OFDM) modulation is used, which implies that the bandwidth is shared among different orthogonal subcarriers [15]. In OFDM systems, CSI explains the propagation of the signal from the transmitter to the receivers, unveiling the impact of scattering, fading, and power attenuation over distance. In the frequency domain, this propagation can be modeled as:

$$Y = HX + N \tag{1}$$

where Y is the received vector, X is the transmitted vector, N is the noise, and H is the channel matrix, also known as CSI. The dimension of H depends on the number of subcarriers S, which in turn relies on the hardware and extraction tools employed.

Several tools and hardware platforms facilitate CSI extraction, including the 802.11n CSI Tool, which runs on the Intel WiFi Link 5300 wireless Network Interface Card (NIC) [16]; the Atheros CSI Tool, which enables the extraction from Atheros WiFi NICs [17]; the ESP32-CSI-Tool developed for ESP32 modules [18]; or the open-source Nexmon Tool, that can be used with Broadcom and Cypress WiFi chips and has allowed CSI extraction employing low-cost Raspberry Pi 3B+ and 4B devices [19].

Regardless of the tool used, the CSI of the single i_{th} subcarrier can be expressed as follows:

$$H_i = |H_i| e^{j \angle H_i} \tag{2}$$

where $|H_i|$ is the amplitude while $\angle H_i$ is the phase of subcarrier i.

Both amplitude and phase information can be used for feature extraction or classification algorithms in different applications. Most crowd-monitoring applications mainly make use of

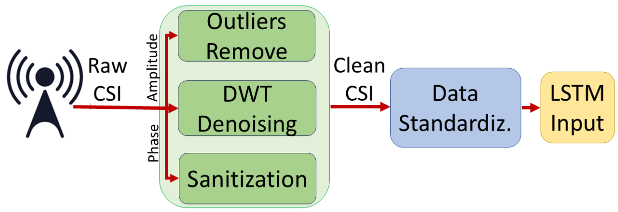


Fig. 2: Data Flow of PC-LSTM Approach

amplitude information, while phase data are generally used in activity and gesture recognition or respiration detection. However, these data are generally affected by noise and outliers' presence. Furthermore, the phase is susceptible to errors such as Carrier Frequency Offset (CFO) and Sampling Frequency Offset (SFO). The first one exists due to the variance in central frequencies, attributed to the lack of synchronization between the clocks of the transmitter and receiver. The second error is instead generated by the receiver analog-to-digital converter (ADC). These errors can be removed through phase sanitization [20].

Therefore, some preprocessing operations are needed before giving the dataset in input to the LSTM Network. More in detail, the preprocessing is divided into the processing of amplitude data and the processing of the phase of the CSI.

The literature has proposed the utilization of different filters and techniques to denoise and remove outliers from the amplitude data. Following [21], in the proposed solution, the outliers are removed by applying a Hampel filter and then denoised thanks to Discrete Wavelet Transformation (DWT), which helps reduce signal distortions. Regarding the phase data, to eliminate the effects of CFO and SFO, the sanitization of the phase is performed through unwinding and linear fitting, following the solution proposed in [20].

After this preprocessing stage, the data is properly cleared and can be used in ML and DL models for crowd monitoring. In the proposed solution, data is standardized and used as input for training the LSTM Network. Figure 2 shows this approach schematically.

In the proposed approach, the input data consists of each subcarrier's amplitude and phase values of all communications links between the TX and RX antennas, observed for T consecutive packets. Therefore, considering S subcarriers and a single link between one TX antenna and one RX antenna, the shape of the LSTM input layer is $T \times S \times 2$.

IV. Reference Use Case

A. Reference Dataset

In order to assess the performance of the proposed approach, a public dataset has been used, i.e. the EHUCOUNT dataset [7].

This dataset contains WiFi CSI measurement in the shape of IQ CSI data for 53 subcarriers collected in 6 different indoor scenarios where up to five people could be present simultaneously. In scenarios ***C***, ***E***, and ***F***, people walked along corridors, while in scenarios ***A***, ***B***, and ***D***, people roamed around a room or hall. The information collected presents real and imaginary CSI data of a 53-subcarrier OFDM symbol. One column of the dataset contains information on the number of people counted in correspondence with the CSI data collected, and this number can vary from 0 to 5. The dataset was collected using a controlled measurement setup, where WiFi signals were transmitted over the 2.4 GHz band using an Anritsu MG3700A vector signal generator, while reception was carried out via an Anritsu MS2690A signal analyzer. In Table I, the information about the number of people for the different scenarios and the amount of data collected for each situation is shown.

TABLE I: CSI traces per class and scenario from [7]

Scenarios	**0**	**1**	**2**	**3**	**4**	**5**
A	14967	13975	13949	13979	-	-
B	14939	13859	12980	14927	15853	14851
C	12932	11982	13867	13881	12983	-
D	12983	13977	13945	13984	14952	12894
E	13975	12973	12978	11979	12975	-
F	14960	14966	14952	14957	14954	14954

Even if the dataset is collected in a controlled environment, as with most datasets related to CSI-based monitoring, it serves as an initial benchmark for assessing the effectiveness of the proposed solution.

V. Performance Evaluation

The PC-LSTM solution is a multi-layer LSTM composed as follows:

1) One input layer.
2) Two hidden LSTM layers of 125 and 100 hidden units.
3) Two dropout layers with a dropout rate of 20%, applied after each LSTM layer to prevent overfitting.
4) A fully connected network layer whose number of neurons corresponds to the number of people expected in the scenario under consideration.
5) A softmax layer, since the softmax function is indicated for multi-class problems with mutually exclusive classes where classes correspond to the number of people to be counted.

The authors in [7] considered time windows of 50 OFDM symbols for feature extraction in the time domain. Hence, given the information recorded in this dataset and the selected time window length, the input layer of the network in our PC-LSTM solution has a shape of $50 \times 53 \times 2$. The dimensions of the fully connected layers depend on the scenario considered in the dataset. Specifically, since scenario ***A*** includes a range of 0 to 3 people, the output classes for this case are 4. Similarly, for scenarios ***C*** and ***E***, where the maximum number of people is 4, the output classes are 5. Lastly, in scenarios ***B***, ***D***, and ***F***, where the number of people can rise to 5, the output targets are 6.

For the Hampel Identifier, a variance of the three-sigma rule of statistics was implemented, and the best results were found using a window of length equal to 3, which means that for each sample, the median absolute deviation (MAD) of the

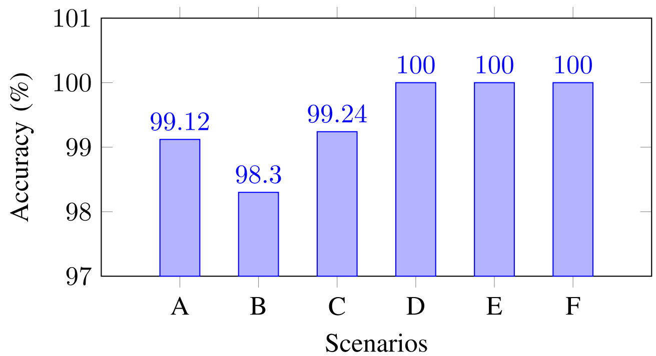


Fig. 3: PC-LSTM Accuracy for Each Scenario of the EHUCOUNT dataset [7].

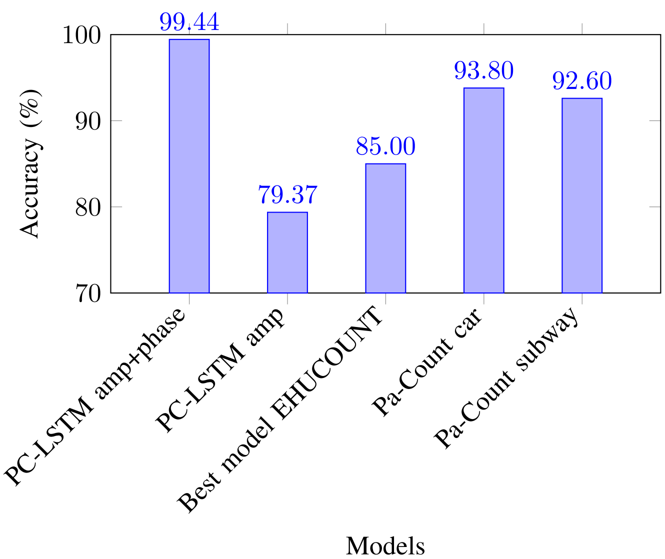


Fig. 4: Comparison of different models in terms of accuracy. Best model results are from Ref. [7], while Pa-Count results are from Ref. [13].

current sample and 3 near samples in either direction has been calculated. To implement DWT for denoising the signal, the chosen mother wavelet was the Symlet wavelet sym6, which provided the best result using a level of wavelet decomposition equal to 5.

For each scenario, a different LSTM network is trained. The training phase is done using 80% of the data. The rest of the data is equally divided for the validation and the test. Preprocessing and training of the models were performed on MATLAB.

Figure 3 shows the results obtained in terms of overall accuracy in classification and, consequently, in people counting for each of the scenarios under consideration. Accuracy is defined as the proportion of correctly classified instances, represented by TP, out of the total instances N within the dataset, expressed as a percentage. Thus, the accuracy formula is given as:

$$\text{Accuracy} = (TP/N) \times 100 \tag{3}$$

From these results, it is possible to see that the PC-LSTM solution achieves great accuracy in every scenario and outperforms the other different machine learning solutions analyzed in [7], where the best model obtained an overall accuracy of 85% for scenario E.

Indeed, Figure 4 illustrates the overall accuracy, calculated as the average across the six scenarios, for the PC-LSTM solution using both amplitude and phase data as explained in Section III-B, as well as using only amplitude data. Since crowd counting typically relies solely on amplitude information, it is particularly noteworthy that performance improves when phase information is also incorporated, provided it is properly sanitized.

For completeness, the same figure also presents a comparison between the PC-LSTM results and those obtained in two state-of-the-art studies. The results clearly demonstrate that PC-LSTM, when leveraging both amplitude and phase information, outperforms the other approaches.

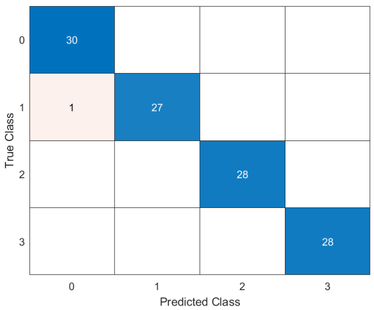
It is interesting to note that in scenarios ***D***, ***E***, and ***F*** the proposed Neural Network reaches optimal prediction performance. However, some classification errors can be observed in the remaining setups. In scenarios ***A*** and ***C***, these errors are attributable to a people count that deviates by, at most, $+/-1$ person from the correct number. In the case of scenario ***B***, an underestimation of -2 people occurred when 3 people were monitored. Indeed, the model predicted a count of 1 while the actual number was 3. These misclassifications can be visualized in the confusion matrices for the three cases ***A***, ***B***, and ***C***, as shown in Figure 5.

To provide a complete overview, Table II summarizes the classification performance, including precision, recall, and F1 score for each individual scenario. As evident from the table, in scenarios ***D***, ***E***, and ***F***, the system achieves perfect scores across all evaluation metrics.

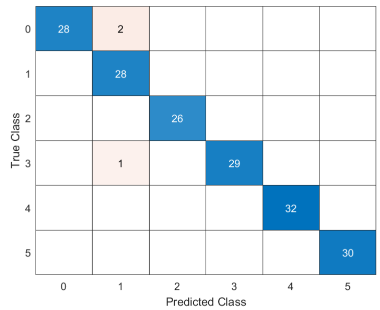
The mobility application envisioned in this paper should accommodate a larger number of people in the scenario; therefore, if the error remains consistently low and in the same range reported here, it is still acceptable for the intended use of this PC-LSTM solution.

VI. Conclusions

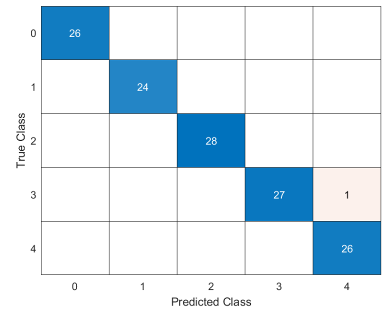
In this study, we presented the PC-LSTM as an innovative approach for real-time people counting in public transport systems. Our methodology leverages WiFi Channel State Information (CSI) to estimate vehicle occupancy without compromising user privacy. The PC-LSTM model demonstrated superior accuracy, outperforming state-of-the-art methods with impressive 99.12%, 98.30%, 99.24%, 100%, 100%, 100% accuracy rate respectively for the scenarios ***A***, ***B***, ***C***, ***D***, ***E***, and ***F*** of the EHUCOUNT dataset. By integrating this technology into public transportation systems, transit operators may enhance service efficiency, improve passenger experience, and support data-driven mobility planning for smarter cities.



(a) Scenario A



(b) Scenario B



(c) Scenario C

Fig. 5: Confusion Matrices for PC-LSTM algorithm considering scenarios ***A***, ***B***, and ***C***

TABLE II: Classification metrics for each scenario based on the confusion matrices

Scenario	Precision	Recall	F1 Score
A	0.99	0.99	0.99
B	0.98	0.98	0.98
C	0.99	0.99	0.99
D	1.00	1.00	1.00
E	1.00	1.00	1.00
F	1.00	1.00	1.00

In conclusion, this research allows for future applications in urban mobility, offering a reliable and privacy-preserving solution for smart city infrastructure. However, it's important to note that these results were achieved under optimal conditions. As part of our future work, we plan to test the PC-LSTM model in real-world scenarios, to understand its performance and robustness outside of controlled environments.

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