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A Machine Learning-based Approach for Vehicular Tracking in Low Power Wide Area Networks

Marco Bertolusso, Michele Spanu, Giovanni Pettorru,
Matteo Anedda, Mauro Fadda, Roberto Girau, Massimo Farina, and Daniele Giusto

***Abstract*—This paper addresses the issue of monitoring and tracking people and vehicles within smart cities. The actors in this work jointly cooperate in sensing, sensible data processing, anonymized data delivery, and data processing, with the final goal of providing real-time mapping of vehicular and pedestrian concentration conditions. The classification of conditions can bring out critical situations that can be communicated in real-time to citizens. Tests were conducted in the city of Cagliari, Italy.**

***Index Terms*—Multimedia for connected cars - Multimedia IoT, Broadcast applications to Smart Cities, Multimedia service deployments, AI for Multimedia Networking Intelligence.**

I. Introduction

Mobility monitoring and control of people and vehicles represents an increasingly considered and high social impact aspect in the management of broadcast services within a smart city. Generally, vehicle presence detection is performed through the use of cameras trained in vehicle shape/type and license plate (LP) recognition. The monitoring of pedestrian flows and presences can also be performed through the use of cameras capable of identifying the occupancy level of a street/square, estimating both the number of people and their directions [1]. In more recent methodologies, the identification of the presence of mobile devices (e.g., smartphones or tablets), equipped with multi-radio interfaces, can be appropriately detected. This approach allows for a more accurate assessment of the flow and number of individuals within an area of interest [2]. It is extremely important how to process data received from different sources and with different characteristics. First of all, it is fundamental to understand how to correlate the number of detected devices with the number of people and vehicles. According to recent statistics, in 2022, the number of smartphone users in the world today is 6.648 Billion, which translates to 83.89% of the world's population owning a smartphone and considering the wide range of essential services that can now be safely accessed through biometric authentication on smarphones [3], [4], this number is only destined to rise. In total, the number of people that own a smart and feature phone is 7.26 Billion, making up 91.62% of the world's population [5]. Wireless localization allows estimating both the location and direction of users and vechicles from the received signal strength (RSSI) and its variation over time, respectively. It seems even increasingly important to have constant monitoring of moving and parked vehicles [6], with a significant impact on air quality [7], [8]. Mobile devices regularly broadcast Wi-Fi requests (i.e., "probe requests") to locate Wi-Fi access points for a potential new connection. A probe request is automatically sent in active scan mode, consisting of the MAC address of the reporting device. A real-time wireless sniffing system detects Wi-Fi packets and analyzes the wireless traffic, providing an opportunity to gain insights into the interaction between humans carrying mobile devices and the environment where they are moving [9].

The second aspect considered in this work concerns the transmission of detected data, some of which fall within the scope of personal data processing according to current privacy regulations. Generally, data can be captured, processed and transmitted free-to-air for further processing, and its storage requires a formal legal procedure. In addition, the collection and storage of sensitive data requires an informative note placed in the area of the surveys, informing users who may be involved in a collection of such data. However, an on-board SHA-512 anonymization technique [10] is employed in this work prior to data submission. Data submission and storage will involve data that has undergone an irreversible anonymization process to protect users. The third aspect treated in this work concerns the transmission technique used to forward the collected data towards a cloud platform. A Low-Power wide area network (LPWAN) is a wireless wide area network solution that counts among its peculiarities a high coverage range, low power consumption, multiple access, low bitrate over a long communication range, the possibilities of developing both private and public networks, and the use of licensed or unlicensed frequencies [11]. Among LPWAN technologies, the unlicensed LoRa [12] is supported by the LoRa Alliance and transmits in different sub-gigahertz frequencies (i.e., 868 MHz and 433 MHz), making it less prone to interference. LoRaWAN is the MAC (media access control) layer protocol that manages communication between LPWAN devices and gateways. These features have allowed the creation of a network composed of LoRa end-points and LoRa gateways equipped with battery power, low power consumption and high coverage range. Data

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sniffed from Wi-Fi/LoRa multi-radio modules is received by the LoRa gateway, which forwards data to a Social-IoT (SIoT) platform named Lysis [13]. The last step consists in data processing through a neural network (NN) in which various machine learning algorithms are trained with the data that characterize the different sources. The output provides real-time monitoring and forecasts on different types of traffic, displayed on a map or on mobile apps allowing real-time alerts to users or public control agencies.
The purpose of this work is to propose a system composed by the sensing layer, allowing to obtain the information about the vehicular and pedestrian flows exploiting the values contained in the fields of the probe requests, and a neural network able to predict the traffic flows of the monitored area.

The rest of the paper is organized as follows: in section II, an overview of state of the art is presented. The architecture and workflow of the proposed method are described in section III. The real scenario to evaluate the performance of the carried out demonstrator and the obtained results are discussed in section IV. Finally, conclusions are drown in section V.

II. Related works

The proposed method in this paper considers the use of machine learning techniques based on convolutional neural networks (CNN) employed in recent applications whenever a classification on certain phenomena is needed through the use of neural networks. Using machine learning to predict extreme events is a major challenge to be prepared for the evolutions that complex systems can undergo. Some fields of application involve environmental, industrial or civic phenomena. For instance, in [14] the authors deal with the uncertainty of the speed and direction of wind that causes wind power prediction to be extremely difficult to wind power generation. The Convolutional Neural Network (CNN) has the advantage of big data processing. CNN addresses data in the form of a two-dimensional matrix and is widely applied in the field of image processing. In this work, a CNN has been applied to wind power prediction. Using the historical data of wind power from a wind farm as input, this work sets and trains the CNN model. The results of the prediction prove the feasibility of CNN applied to regression prediction. An interesting field of application concerns the classification of environmental sounds by means of a CNN. In [15] the authors adopt an efficient convolutional network architecture for urban sound classification, and a series of experiments with different network inputs has been conducted. The results of the experiments suggest that the best classification performance on urban sounds is usually obtained when the input spectrograms have moderate temporal resolution, especially for those sounds with relatively short temporal structures. Accurate prediction of intercity traffic flow has been one of the most important global issues in road traffic congestion research. Since the intercity traffic information presents a challenging situation, traffic flow prediction involves a rather complex nonlinear data model. In recent years, the support vector regression (SVR) model has been widely used to solve nonlinear and time series regression problems. In accordance with this premise, the authors in [16] presented a short-term traffic prediction model that combines the support vector regression model with continuous ant colony optimization (SVRCACO) algorithms to predict intercity traffic flow. The prediction results indicate that the proposed model provides more accurate prediction results than the seasonally integrated autoregressive time series model (SARIMA). Therefore, the SVRCACO model is a promising alternative for traffic flow forecasting. In another approach the authors in [17] use a Wireless Sensor Networks (WSNs) consisting of a large number of sensor nodes. Each node is empowered by a communication interface that is mainly characterized by low power, short transmission distance and minimal data rate (e.g., the maximum data rate in ZigBee technology is 256 kbps, while approximately the physical transmission range between 10 to 20 meters). Currently, WSN Technology is being distributed over a large roadway of areas, in order to monitor traffic and environmental data. This approach allows several Intelligent Transport Systems (ITSs) applications to exploit the primary collected data in order to generate intelligent decisions based on earlier valuable selected information. Furthermore, in [18] the authors focus on utilizing Wi-Fi based road-side sniffers to listen to Wi-Fi probe signals broadcasted by the smartphones present inside vehicles for estimating traffic stats of road segments. Hopping Interval (HI) is the rate at which Wi-Fi radio of the sniffer is changed to one of the available channels in ISM band. A channel hopping algorithm is proposed, which adjusts HI of the sniffer according to the current traffic conditions. The proposed algorithm reduces the estimation error and increases the robustness and efficiency of the traffic monitoring system. A key aspect to be considered when designing these kind of systems represents the use of transmission technology. The chose varies according to the specifications of the system and the requirements in terms of performance. IoT technologies in a Smart City can be summarized in two typology: fixed and short-range or long range technologies. Our system need long range technologies like LoRa WAN, Sigfox or cellular technologies like GSM, LTE or 5G [19]. In a Smart City environment and in the proposed scenario, a transmission technology that allow low power consumption and long range coverage is needed. These requirements are satisfied by LPWAN (low-power wide-area network) technology, of which LoRa is one of the precursors. For our system we decide to rely on LoRaWAN technologies that guarantees long-range communication from 10 to 15 kilometers in an outdoor environment and very low power consumption that enable the use of battery-powered devices. LoRaWAN network architecture is deployed in a star topology in which gateways relay messages between end-devices and a central network server. The gateways are connected to the network server via standard IP connections [20]. The reference architecture is shown in figure 1. LoRaWAN perfectly suit with the devices used in our proposed system that are resource constrained, battery-powered and must cover long ranges. Given the limitations of the works in the literature related to vehicular tracking, our system aims to overcome them through

an approach based on Machine Learning through the use of a neural network.

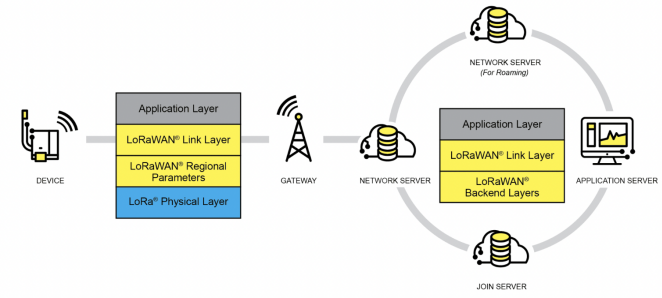


Fig. 1. LoRaWAN Network Architecture [20]

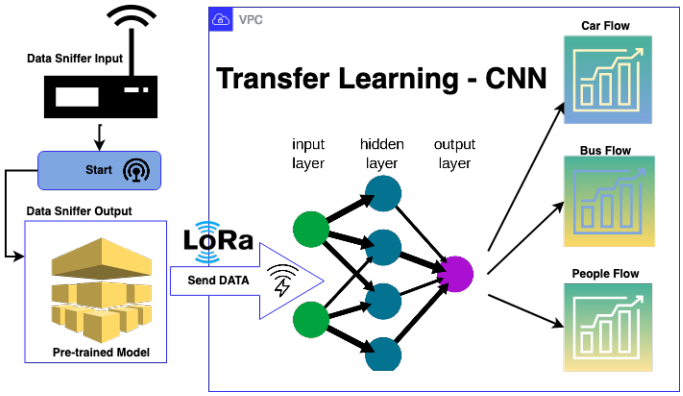


Fig. 2. Block Diagram.

III. Proposed Method

The aim of our proposal is to use the data device acquisitions for the construction of an neural network pre-trained model able to predict the traffic flows of the monitored area. First of all, the acquired data by Wi-Fi sniffers return the information related to:

- Signal strength;
- Power decay time;
- Density of detected devices.

The above mentioned informations represent the features that have been used for the construction of the pre-trained model for any monitored area. These models are able to return the speed of the detected devices. Once each sniffer in a given area has acquired the traffic flow data, the identified devices are assigned to three speed classes. These three classes are used to build the pre-trained model which is then sent via LoRa to the cloud platform. The three-class model, one for each sniffer, represents the input layer of the neural network and is used to train it.

The three classes are defined as follows:

- Pedestrians [0 - 20 km/h];
- Cars [20 - 60 km/m];
- Bus [20 - 60 km/m + high density of devices].

The three resulting classes are used to build the convolutional training model which, once trained, will be able to make predictions about the traffic flows of the areas monitored by the sniffers. Fig. 2 shows the block diagram of the system, where it can be seen how the sniffer system acquires the data of the monitored area and returns a pre-trained model as output which is sent via LoRa to a cloud platform, for subsequent training of the neural network target located inside the platform itself. The procedure to follow for the initialization of our system require the four steps listed as follow.

- STEP 1 - LOAD WEIGHTS: in this phase the pre-trained models are used to load the weights of the neural network, in order to initialize it;
- STEP 2 - MODEL TRAINING: once the neural network is initialized, it is necessary the training step. The training phase is carried out by using a synthetic dataset properly created from holistic data and containing traffic monitoring data obtained from an hybrid system [21]. Finally, cross-validation must be performed in order to optimize the performance of the model;
- STEP 3 - USE PRE-TRAINED MODEL: once the neural network has been trained and validated, the pre-trained model used to load the weights is continuously updated (Transfer Learning Method), learning after each prediction;
- STEP 4 - LAUNCH TRAINED NN FOR PREDICTION: the last step consists to test the entire system in a controlled scenario to verify its accuracy.

IV. Setup Environment and Results

The geographic area involved in our study represents a reference basin for the entire territory of the Metropolitan Area of the city of Cagliari (Italy), in which, in addition to important residential settlements, are located all the main services, production activities, poles of attraction and generation of transport demand. The system has been installed in an urban area including different types of crossroads, medium-fast city streets and slow roads in residential areas. In free-flowing areas, congestion problems involve large concentrations of vehicles or the presence of special conditions such as motor vehicle accidents or the simultaneous passage of several modes of public transportation. In residential areas the crossroads are a confusing labyrinth of one-way slow speed (30km/h limit). In this context the congestion of vehicles is much more complex, related to the habits of residents as the continuous passage for home collection of solid urban waste that inevitably block the road system. For these reasons, the system has been designed to classify the different types of vehicles and activities carried out in the road context. In this way we were able to create a monitoring system of the areas to predict the routes of, for example, the means for garbage collection and offering in real time the possibility of taking an alternative route within the residential area, avoiding unnecessary blocks and delays along the way. It is important to note that the congestion of residential areas is one of that causes the most inconvenience to citizens and the greatest harmful emissions into the environ-

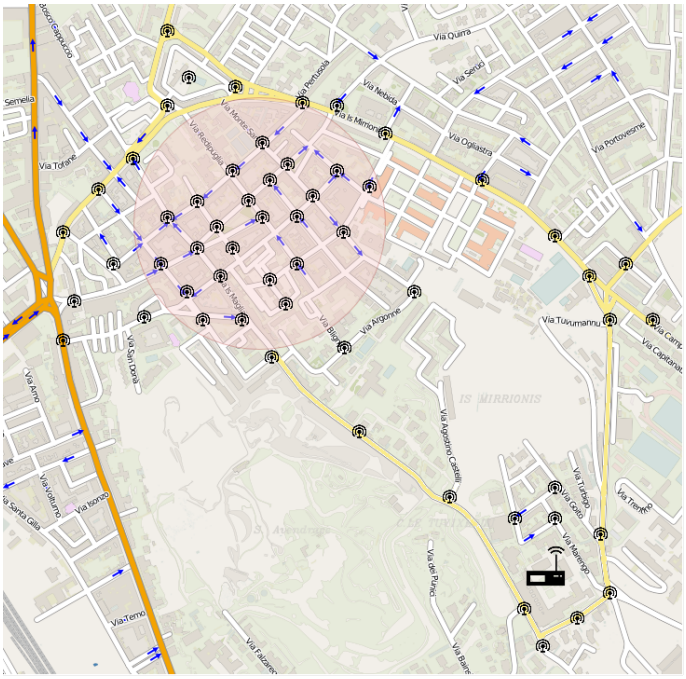


Fig. 3. Coverage of the area of interest.

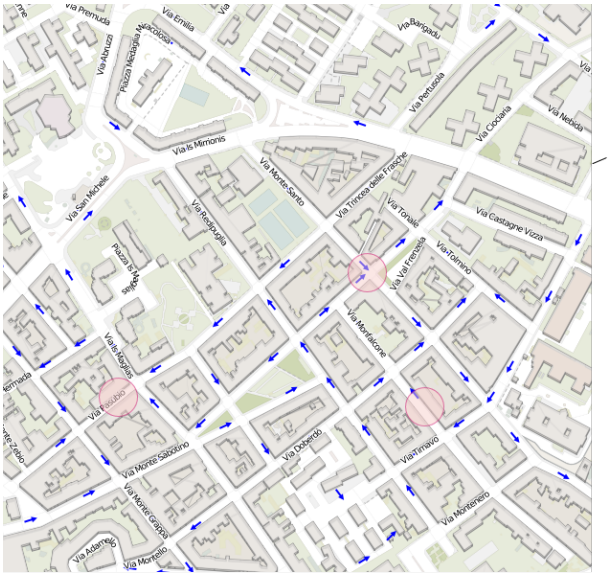


Fig. 4. Location of waste collection vehicles at work



Fig. 5. Previsioned status of path

ment as the means are forced to a continuous start and stop. In medium-fast flow areas, the system is able to suggest in real time both alternatives through the same type of road and non-congested alternative routes through residential areas at the main crossroads. The map in Fig. 3 shows the monitored area, where the yellow highlight lines on the map represent the medium fast roads, whereas the red highlighted area is the residential area. As we can see, most of the sensors are located within the residential area, the choice of LoRa technology was essential because the environment is characterized by buildings relatively high compared to the position of our equipment which generates a tunneling effect that forces us to work suitable for NLOS. This technology allows us to make the nodes communicate with each other and at the same time transmit data to the LoRa base station located near the Faculty of Engineering of Cagliari, on top of a hill. It is interesting to note that the number of sensors increases inexorably as the number of streets involved increases. Medium and fast flowing roads have considerably less need of sensors to be monitored and these are located at the main road junctions.

In the following scenario a test has been carried out by setting a starting and ending point. The red colored areas in Fig. 4 represent the presence of means of urban waste collection in door-to-door mode while the blue arrows represent the one-way residential street. Due to the increased adoption of garbage division and recycling, the presence of vehicles is continuously increasing. The vehicles involved in our analysis are zero impact as they are equipped with an electric motor. This aspect involves both small to medium-sized vehicles such as the above mentioned, and larger ones such as buses, thanks to the awareness of the city of Cagliari (Italy) towards respect for the environment and a and a more eco-sustainable city. When a refuse collection vehicle travels along an internal road to perform collection work users are informed of their location, the route they will take, and the best route to bypass them. The best route is calculated on the information continuously exchanged within the sensors network, and thanks to the algorithms of prediction running in the cloud, the system is able to analyze and recognize the behaviours of different flows and provide the best guidance accordingly.

Let's assume that the initial condition is the one shown in Fig. 5: in this scenario the system has worked out the best route at this current instant of time. Proceeding along the path, also the other vehicles involved in the area will move accordingly.



Fig. 6. updating map during the transit

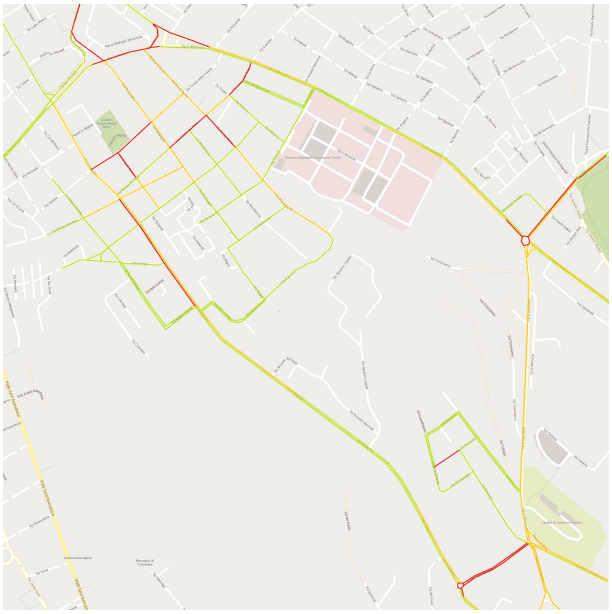


Fig. 7. Vehicular flows at a particular time

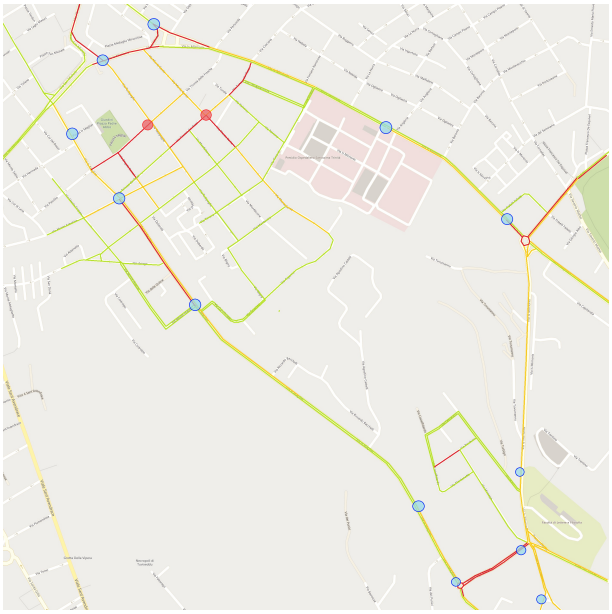


Fig. 8. detail from map layers, flows, buses, dustman

When the system senses a possible slowdown, it warns the user and modifies the ideal path. The prediction is realized in the cloud and forsees the movements of the vehicles in advance. In case of unforeseen movements or delays in transit, the system automatically updates itself providing the users with the new routes. It is possible to appreciate the behavior of the system with the evolution of the scene in the Fig. 6. We can notice that the system promptly reworks the route based on the knowledge of the behavior of the garbage collectors working in the internal roads. This allows us to provide the user with a new route with respect to the one initially estimated well in advance of the transit in the route. These features are essential during peak hours, when citizens and waste collectors share the road most. The proposed system has economic and social benefits, reducing road occupation time and the accumulation of stress due to traffic. Furthermore, the system offers indications on the best routes to the waste collection service in order to optimize times and orchestrate their movements within the residential areas. Regardless of the route we want to travel, the system is able to generate a map representing the condition of all road sections. As shown in Fig. 6, in every moment it is possible to know the conditions of the different flows. The different colors represent the traffic intensities: green indicates a free road, orange average occupation with possible slowdowns, while red indicates heavy traffic and heavy slowdowns. The generation of the map is on levels, selecting for example the public transport as in Fig. 7 and Fig. 8 it is possible to select the buses and the working vehicles. In Fig. 8, we can appreciate the position of the buses represented by blue moving areas in the map. The impact on the flow of public transport vehicles depends greatly on the number of bus routes that pass along the paths. In the area there are in fact some lines that have a significant impact as they are used by a high number of users (citizens, students, workers) that force the vehicles to repeatedly stop and block traffic. Other less used lines have a much lesser impact and sometimes do not even make a stop in the absence of users. The two types of public buses are identified by the system and, depending on the behavior adopted, they will or will not have an impact on traffic, as foreseen by our system. Finally, table I shows the details of the scenario monitoring and an initial comparative analysis between the actual data and the data predicted by the proposed system and the data classification by the employed neural networks.

TABLE I
PEOPLE AND VEHICLES DETECTION

		Predicted Data			Sum
		Cars Flow	*People Flow*	*Bus Flow*	
Real data	*Cars Flow*	1024	11	41	1076
	People Flow	18	2946	53	3017
	Bus Flow	12	13	54	79
Sum		1054	2970	148	4172

V. CONCLUSIONS

The high concentration of activities and settlements involves a road system characterized by consistent daily vehicular flows, which in the peak hours cause congestion with consequent extension of travel times and conditioning of accessibility to the city. The simultaneous management of distributed LoRa end-points equipped with Wi-Fi sniffing has provided a huge amount of data concerning vehicular mobility. The proposed system exploited convolutional neural networks (CNN) with a pre-trained model from the real-time sensed data. The novelty introduced therefore made possible not only a monitoring, but a prediction model of vehicular flows with a machine learning based approach. The tests conducted showed the validity of the proposed system, in comparison with conventional monitoring systems not suitable for predictive analysis.

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