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Passenger BIBO detection with IoT support and machine learning techniques for intelligent transport systems

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Abstract

The present article discusses the issue of automation of the CICO (Check-In/Check-Out) process for public transport fare collection systems, using modern tools forming part of the Internet of Things, such as Beacon and Smartphone. It describes the concept of an integrated passenger identification model applying machine learning technology in order to reduce or eliminate the risks associated with the incorrect classification of a smartphone user as a vehicle passenger. This will allow for the construction of an intelligent fare collection system, operating in the BIBO (Be-In/Be-Out) model, implementing the "hands-free" and "pay-as-you-go" approach. The article describes the architecture of the research environment, and the implementation of the elaborated model in the Bad.App4 proprietary solution. We also presented the complete process of concept verification under real-life conditions. Research results were described and supplemented with commentary.

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1. Introduction

A smart city supports sustainable economic development and a high quality of life of its inhabitants. This is effected through investments, including those in modern communication, understood both as transport and IT [7]. One of the constituents of this type of city is an intelligent public transport and toll collection system. Such a system is expected to limit the activities of the passenger related to the collection of fare, and in particular, signaling the fact of starting and ending a journey by a public transport means [26]. The classic approach to travel settlements involves the use of a paper ticket or electronic card and the selection of the appropriate tariff on the device for charging fares (the so-called ticket validator). This requires the passenger to validate their ticket or take out their card at the beginning of their ride, and to repeat the card operation at the end thereof, in order to correctly process payment for that ride. This approach is the implementation of the CICO (Chack-In/Chack-Out) model source [22], [30]. With the development of mobile tools, including mobile phones (smartphones) and Internet technologies, including cloud computing - new services are implemented, supporting the hands-free and pay-as-you-go approach. The first provides great comfort for the user, as all that is required to access the service is that you have your phone with you. Users no longer not need to hold the phone in their hands to be able to use a broad range of services. The "pay-as-you-go" approach allows the operators to charge only for the time the service is actually used for. The carrier of such a service is a mobile device with an application provided in the SaaS (Software as a Service) model. The development of technology has also influenced the separation of the IoT (Internet of Things) area, with development of beacon type transmitters and mobile devices, such as smartphones and smartwatches, and their communication modes sources [4], [20], [23], [28]. Novel technological options laid the cornerstone for an attempt to automate and improve the efficiency of the CICO model in public transport fare collection systems. Launched in 2017, the research and development project entitled 'Innovative concept of toll collection and settlement for municipal services under SmartCity' had the objective, among others, of building a convenient "hands-free" and "pay-as-you-go" travel system, using sensors and controllers along with modern mechanisms of information analysis and correlation [3].

The purpose of the present article is to report selected research results, as obtained by the authors during the implementation of the research and development project, and concerning the possibility of automating the CICO (Check-In Check-Out) process of the fare collection system and replacing it entirely with a BIBO (Be-In/Be-Out) model. We present a concept of an integrated passenger identification model using the Internet of Things devices such as beacons and smartphones, as well as machine learning technology.

The first section of our article describes research that provides complementary knowledge in the subject area of the article. Then we go on to describe the research problem and its solution. We described the architecture of the research environment and the implementations of the developed model in the proprietary Bad. App4 solution. We also presented the complete process of concept verification under real-life conditions. Research results were described and supplemented with commentary.

2. Reference approach

For a long time now, public transport systems used fare collection solutions, which in order to collect and account for the fare utilized paper tickets, and, optionally, a document confirming the entitlement for discounts in the said fare rate. Together with the development of technology, solutions streamlining the fare collection process began to appear. Concepts for electronic ticket-based systems appeared first developing substantially over the last two decades [6], [15] [17], [29]. They applied electronic - microprocessor card (smartcard) technology to store the passenger ID and ticketing data. Initially, just like paper tickets, electronic tickets required the passenger to actively validate the ticket – that is why when boarding the vehicle, we had placed our card on a card reader (Check-In, CI action). For some types of tickets (e.g., those taking transfers between vehicles into account), it was also necessary to notify the system about the end of the journey by contacting the card with the reader when leaving the bus (Check-Out, CO). The manual ticket validation process has adopted the acronym CICO originating from its full Check-In/Check-Out wording.

Further development of this model adopted various variants, e.g., transferring an electronic ticket to mobile devices or adding electronic purse services to the electronic ticket, enabling direct payment for the commute.

The automation of the CICO process was an essential step in the development of fare collection systems. Manual ticket validation was gradually phased out by automated validation processes, e.g., after Be-In detection of the boarding passenger, or Be-Out detection of a leaving one. The automatic CICO process was thus described by the BIBO acronym. The report entitled "Be-In-Be-Out Payment Systems for Public Transport" analyzes the projects, which already in the mid-1990's described the process of automatic detection of passenger presence in the vehicle [11]. The described processes applied specialized contactless smart cards, which were used as an identifiable element for the devices located on board of the vehicle. Later projects utilized dedicated devices or phones that were turned into electronic tickets.

The authors of the present publication note a significant step in the development of the BIBO model with the arrival of the Internet of Things (IoT) and Machine Learning (ML) technologies, which according to the Forbes Technology Council may constitute the most important technological trends of the coming years [9]. It is assumed that the Internet of Things includes all identifiable devices that are connected to the network, and can communicate with each other. Among them, we may list transmitters, e.g., beacons that emit an identifiable signal and receivers, such as e.g., smartphones that are capable of receiving such a signal. Subject literature contains research on the possible applications of these types of devices in transport. Among others, Narzt and his associates analyzed the use of beacon and smartphone devices supporting the Bluetooth Low Energy BLE radio signal in the automation of the fare collection process [18]. What they demonstrate is the possibility of implementing the BIBO (Be-In Be-Out) process using these devices and RFID (Radio Frequency Identification). Another topic that coincides with the research presented in the article is the use of a smartphone device and in particular its sensors, in the context of building the passenger behaviour profile. Research on monitoring the behaviour of drivers using their phones was carried out by the team led by Singh and Kanarachos [13], [24]. They demonstrated the possibility of applying sensors such as leverages gyroscopes, accelerometers, and GPS to collect data on user behaviour.

In recent years, Artificial Neural Networks (ANNs) have been widely adopted to analyze large volumes of data in various areas, including the research area of transportation and travel behaviour. According to the authors [12], [27] currently ANNs are mostly used to analyse observed movement patterns and to make short-term travel demand predictions. Other researchers concentrate on travel time estimation, driving behaviour detection, traffic state classification [10]. Omrani compared Support Vector Machines (SVM) and Logistc Regression (LR) to ANNs for travel mode choice prediction among three categories (car, public transport, walk, or bike) [19]. The result showed that the ANN performed better compared to other alternatives. ANNs are also widely used for vehicle classifications, a vast range of research concerns classification of vehicles detected from images [1], [5], [8], [14], [21]. The authors of presented a system to classify different vehicle categories (bike, rickshaw, car, bus) based on smartphone sensor data (accelerometer, gyroscope, orientation, GPS, magnetometer, light, microphone), they compared the performance different ml methods (decision trees, K Nearest Neighbor, Hidden Markov Model, Support Vector Machine and Naive Bayes) [10]. Decision tree outperformed other classification algorithms. Simoncini performed three-class vehicle classification (light-duty, mid-duty, and heavy-duty) with deep learning neural network architecture based on GPS data [25]. The aforesaid researches form complementary knowledge for the area of the present article.

3. Problem definition

Research carried out as part of the research and development project demonstrated that it is possible to implement the BIBO model consisting in automatically detecting the presence of a passenger in a vehicle, assuming that the vehicles will be identified with beacons and the passengers will have a smartphone type mobile device with the BadApp application installed [16]. What was also proven, was the ability to collect information that identifies the behaviour of a mobile device user as a passenger of a specific type of vehicle. To prove the effectiveness of the BIBO passenger model, it was necessary to completely eliminate or minimize the risk of incorrect classification of the user as a vehicle passenger. This risk was present whenever the user was moving on board of another vehicle, or on foot, next to a vehicle he was detected "in". In order to solve this issue, we decided to build an integrated model combining the BIBO model and the user behaviour model. The model was supplemented with vehicle type submodel (vehicle type dictionary) and vehicle route, as determined on the basis of the data of the City Transport Authority timetables, and preliminary algorithms for calculating the distance between the user and the nearest stops of the respective type added. Two hypotheses were formulated in the study:

1. Is it possible to build an integrated passenger identification model based on user behaviour models, vehicle routes, BeIn-BeOut activities and predefined relationships between data that will allow for automation of fare collection and implementation of the "hands-free" and "pay-as-you-go " concept of fare?

2. Will the integrated passenger identification model using machine learning mechanisms allow for the correct identification of the user as a passenger traveling by a specific type of vehicle (bus, tram, train) at an accuracy level of above 90% in real-life conditions?

Therefore, the combination of the submodels into a comprehensive, integrated passenger identification model, which was presented in Fig. 1, proved to be a formidable challenge.

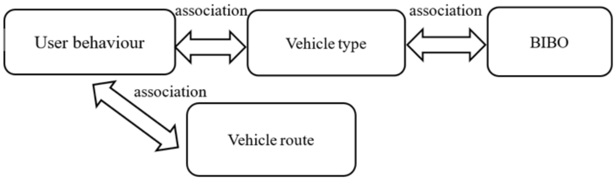


Fig. 1. The integrated passenger identification model. Source: [authors' own elaboration].

It required determining the final scope of acquired and analyzed data (**Error! Reference source not found.**.) and a way to establish relationships between submodels. Three types of relationships were established:

1. The connection of the functional relationship between the Vehicle Type and BIBO submodels - is the relationship between the BIBO submodel and the list of defined public transport vehicles that belong to a specific type of vehicle (bus, tram, train). Identification of a specific vehicle, e.g. bus no. 5 is made on the basis of the signal of its beacon. This, in turn, makes the system receive information about vehicle type;
2. The connection of the functional relationship between the User behaviour and Vehicle route submodels - consists in enriching data on user behaviour with additional data concerning its position in relation to identified stops in the post-processing stage.
3. The connection of the probabilistic relationship between the User behaviour and vehicle type submodels were based on the results obtained in the process of training a multilayer sequential neural network.

Table 1. Data range, the submodels, and their sources of origin. Source: [authors' own elaboration]

No.	Data	Submodel	Source
1	accelerometerDataX	Zachowanie użytkownika	smartphone
2	accelerometerDataY	Zachowanie użytkownika	smartphone
3	accelerometerDataZ	Zachowanie użytkownika	smartphone
4	accessPoint_closestId	Zachowanie użytkownika	smartphone
5	accessPoint_distanceOfClosetst	Zachowanie użytkownika	post processing
6	accessPoint_powerOfStrongest	Zachowanie użytkownika	post processing
7	accessPoint_strongestId	Zachowanie użytkownika	post processing
8	access_Points_No	Zachowanie użytkownika	post processing
9	activityType	Zachowanie użytkownika	smartphone
10	deviceId	Zachowanie użytkownika	smartphone

11	distanceToClosestStation	Marszruta pojazdu	post processing; smartphone latitude, longtitude, z pliku ZTM położenie X i Y przystanków
…..	……	…..	…..
41	transportType	Typ pojazdu	smartphone, post processings
42	transportTypeFromBeacon	BIBO/ typ pojazdu	smartphone
43	lineFromBeacon	BIBO/ typ pojazdu	post processings
44	timeDifferenceToLineClosestStation	Marszruta pojazdu	post processings
…..	……	…..	…..

The integrated passenger identification model (without connection no. 3) was implemented in the research solution in the form of the Bad.App4 mobile application (described in the subsequent chapter) in the data collection mode. The developed mode enables data acquisition in the context of vehicle types (data range Tab. 1), constructing connection nos. 1 and 2 between that data, and then transferring data and connections to the central system. All variables marked as "post processings" are created in the mobile application. The construction of a fully integrated passenger identification model also containing the connection no. 3 was possible thanks to the development of the proper correlation between the User Behavior and Vehicle Type submodels. The correlation is determined on the basis of the perceptron learning algorithm of neural networks, after feeding them with data describing the user's behaviour. The research was carried out on two sets of neural network models trained on data sets differing in the number of their records. The sets consisted of 5 models, differing in input data, all other network parameters were identical for all models. The networks were based on the PYTHON programming language and machine learning libraries: Keras (Tensorflow framework). Network parameters with matching levels are presented in Tab 2.

Table 2. Parameters of network 1 and network 2. Source: [authors' own elaboration]

	Layer 1	Layer 2	Layer 3	Layer 4	Number of Epochs
Number of output neurons:	64	32	32	7	120
Bias:	yes	yes	yes	yes	
Activation function:	relu	relu	relu	softmax	

20 743 samples were used to train the first set of neural networks, including the following numbers of entries from public transport vehicles: bus 7 966, tram 6 525, train 619, and following numbers of entries from alternative modes of mobility: car 598, bike 81, foot 598 and 4 444 unassigned ones. Samples were collected during 107 trips, in total, we performed 31 bus trips, 31 walking trips, 19 trips by car, 18 by tram, ten by trains, and four riding a bicycle.

To train the second set of neural networks, we used 43 334 samples (expanding the previous set of samples) including the following numbers of entries from public transport vehicles: bus 13 511, tram 8 701, train 1 260, and entries from alternative modes of mobility: car 1 422, bike 649, on foot 3 374 and 14 417 unassigned ones. The samples come from 290 different trips, with 118 trips by bus, 77 on foot, 49 by car, 34 by tram, 20 by train and 12 by bike, respectively.

Each set consisted of 6 models of neural networks. The models differed in the scope of applied features (columns). Before training the model, the data was validated by removing all entries that contained any empty values for the record elements that the model was considering. This led to a reduction in the training set, with less data passing the validation for the more extensive models. For example, for network 2, model 1 was trained on 31760 samples, and model 2 on 25471 samples only (a training data set containing some 20% less records). Model 1 was based primarily on data generated from cell phone sensors; which included information from the accelerometer, gyroscope, magnetometer, light sensor, sound pressure sensor, gravity sensor and barometer. In addition, the model analyzed information about the number of WiFi access points detected - access_points_No (Tab. 1). Model 2 analyzed all the characteristics of model 1 and the characteristics concerning access_points, such as the distance from the nearest access point and the received signal strength for the strongest point. Model 3 applied the features of model 2, and additionally retrieved information about the type of activity generated from 6Iuet Api (the name of the variable in the model is activity type) [2]. Activity_Type adopted one of the following values: IN_VEHICLE, STILL, WALKING, ON_BICYCLE, RUNNING, NO_INFORMATION. For each of the listed values, a column was generated containing the 0/1 flag type information. Model 6 has been expanded in relation to model 3 by the user's longitude and latitude sourced from the GPS sensor, as well as the speed of travel, as calculated on the basis of two subsequent samples. Model 4 had all the features of model 6, and it additionally used information about the position of public transport stops in Warsaw. The information analyzed concerned the distance to the nearest stop and a list of distances to the nearest stop, broken down into types of vehicles stopping at the respective stop. In this way we received distance_LINETYPE columns for 12 types of public transport lines. Model 5, the most restrictive one, used information about the number of the line sourced from the beacon. On this basis, it was looking for the nearest stop for this line, and the model included the distance from this stop and the time difference between the present time and the nearest departure of the vehicle of this line from this stop.

A significant reduction of the training data set was observed during the data validation process for models 1 and 2, for both networks. On this basis, the decision was made to modify the model 3 by abandoning the data on WiFi access points. This allowed testing a modified model that was trained on a larger data sample. In this way, satisfactory results were obtained, consisting of increasing the effectiveness of assessing the quality of the model by several tenths. The application of this approach for subsequent models did not bring similar results, because the models were more restrictive, and the removal of WiFi access points did not significantly increase the training set.

Table 3. The scope of additional data downloaded by BadApp4 (test mode) sent to the central system queue. Source: [authors' own elaboration]

The scope of data sent to the central system queue
Number of the implemented scenario, e.g., S1, S2
Means of transport identified on the basis of beacon one of (tram, bus, train)
Model 1, Means of transportation 1 on foot, probability
Model 1, Means of transport 2 tram, probability
Model 1, Means of transport 3 bus, probability
Model 1, Means of transport 4 train, probability
Model 1, Means of transport 5 car, probability
Model 2, Means of transportation 1 on foot, probability
Model 2, Means of transport 2 tram, probability
Model 2, Means of transport 3 bus, probability
Model 2, Means of transport 4 train, probability
Model 2, Means of transport 5 car, probability
Model 3, Means of transport 5 car, probability
....
Actual means of transport, e.g. Foot - indicated by the tester

These networks that fully implemented the connection of relations between the submodels of: User behaviour and Vehicle type were then implemented in the test mode of the Bad.App4 research application. This mode enables the collection and analysis of comprehensive data and relationships of the integrated passenger identification model. The test mode of the application sends 47 variables, as defined in Tab. 1, to the central system, and also additional information on prediction, as described in Tab. 3.

4. Architecture of the research environment

For the purposes of the study, we developed the Bad.App4 mobile application, which became an element of the entire research environment, and its architecture is presented in Fig. 2.

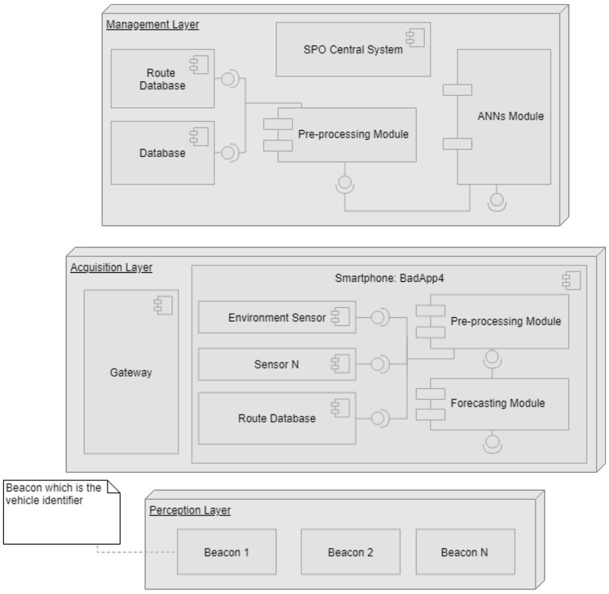


Fig. 2. Architecture of the research environment Source: [authors' own elaboration].

The research environment consists of three main layers. The perception layers are responsible for connecting "things" to the system and sourcing data from them. In this context, beacon devices are used to identify the vehicle found in the user's space.

The next layer (acquisition) is responsible for acquiring data from the lower layer, supplementing it with further data available in this layer, and transmitting this data to the upper management layer. This layer includes two components, which are the mobile device equipped with the BadApp.4 application and a gateway. The Gateway component symbolizes devices such as a router or switch, enabling the connection of the mobile device to the Internet, and thus to the management layer and the central system. The second highlighted element of this layer (acquisition) is the BadApp4 application installed on a mobile device. The main BadApp4 elements highlighted in Figure 2 are:

- Sensors - such as the gyroscope, accelerometer, sound level sensor, and other, described in Tab. 1.
- Route Database - containing data on routes and stops.
- Pre-processing module - responsible for generating parameters concerning the convergence of user behaviour with the timetables, based on data from the GPS sensor, information on the time of sample acquisition, and data from routes.
- Forecasting module - responsible for the prediction of user behaviour, based on the classification resulting from the activity of neural network models operating in the central system.

The last layer is the management layer. Its primary purpose is to store and process the collected data. It also provides access to standardized data for other devices, via established interfaces. The management layer is based mainly on the central server, which is designed to collect data sent by passengers' mobile devices. It also contains a module responsible for training neural network models (Multilayer Perception - MLP), used to determine the presence of a passenger in a vehicle. The main elements of this layer are:

- Route Database and Database - containing data about routes and data from sensors of the users' devices, respectively.
- Pre-processing module - which, similarly to that of the acquisition layer, is responsible for generating parameters concerning the convergence of user behaviour with the timetables, based on data from the GPS sensor, information on the time of sample acquisition and data from routes. This, in turn, serves the use of these parameters in training the neural network.
- ANNs Module (Artificial Neural Network module) - responsible for the training of the defined MLP models.

After previous market research, we managed to determine that the perception layer will be built using the Beacon Pro devices provided by Kontakt.io., which are utilizing the iBeacon protocol in the process of communication with the acquisition layer. The acquisition layer was applied on smartphones with Android Nougat (7.0) and Oreo (8.0) versions. We used several types of phones in our research: LG G6 - Android Oreo, CAT S41 - Android Nougat, Huawei Mate 10 pro - Android Oreo, and Samsung A5, all of which supported BLE. The proprietary mobile software Bad.App4 was written in JAVA and Kotlin.

5. Research process

In the second quarter of 2019 we carried out a test of the effectiveness of recognizing passenger travel in real conditions. The test was carried out in the city of Warsaw Poland, based on the general scenario and 25 specialized scenarios (see Tab 4).

Table 4. An example of a specialized test scenario. Source: [authors' own elaboration]

Scenario 1:
Follow points 1-4 of the instructions;
According to point 5. activate the beacon for Line 4 (tram);
Perform points 6;
Enter the S1 number according to point 7;
Set the means of transport as "Tram" in accordance with point 8;
Get on the Line 4 vehicle (tram) and follow point 9;
Drive a Line 4 vehicle (tram) one stop (about 3-10 min);
Get out of the vehicle and follow point 10.

The scenarios were developed in such a way as to test the most likely events that may occur for a person who has a smartphone with an installed and running application for charging for traveling by a public transport vehicle, e.g., bus/tram/train. The matrix of scenarios is presented in Tab. 5. In every scenario, the system reads and identifies the beacon belonging to the specific vehicle. This forms the basis to charge the fare. Before charging a fee, the system verifies the likelihood that the user is actually travelling on a particular type of vehicle. To compare the correctness of the forecast with the actual condition, the tester indicates the type of vehicle her or she is travelling with during the test.

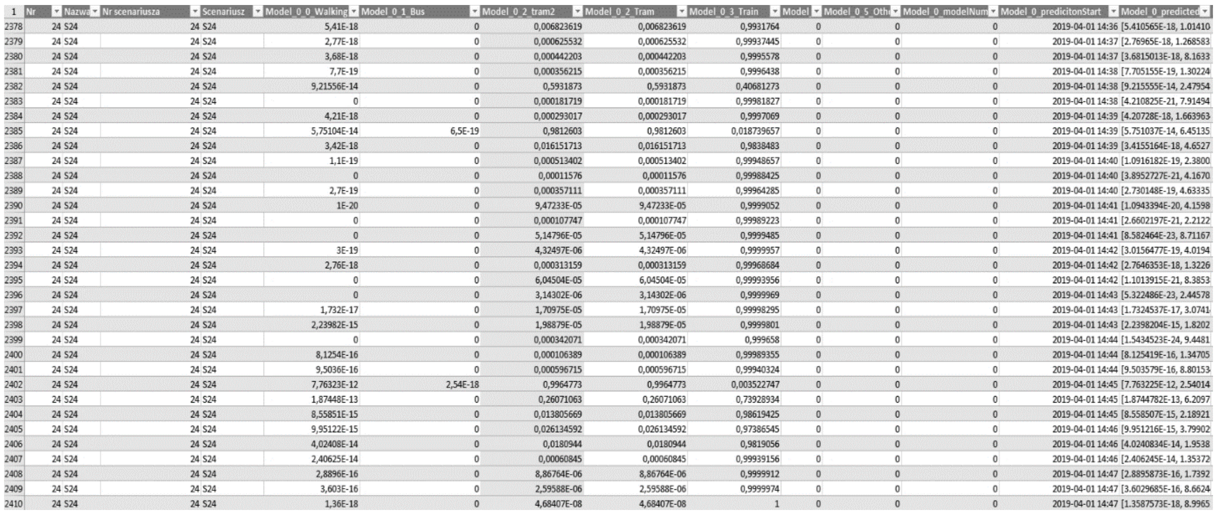
Table 5. Test scenario matrix for the detected - actual type of vehicle arrays. Source: [authors' own elaboration]

	Real									
Read from a beacon	Line_4 (tram)	Line_17 (tram)	Line_18 (tram)	Line_174 (bus)	Line_217 (bus)	Linii_127 (bus)	Linie_S2 (train)	Walking	Bicycle	Car
Line_4 (tram)	S1	-		-				S4	S22	S23

Line_17 (tram)		S2		S8				S5		
Line_18 (tram)	S9		S3					S6		
Line_174 (bus)	-	S7		S10				S14		
Line_217 (bus)					S11			S15	S20	S21
Line_127 (bus)						S12	S19	S16		
Line_S2 (train)						S18	S13	S17	S24	S25

The scenarios were divided into three groups:

- scenarios (S1, S2, S3, S9, S10, S11, S12, S13) - the user travels on the type of vehicle in which he has or she was identified by the system (e.g., for S1 he or she was identified in tram line 4, i.e., in the correct location). The system is to confirm his or her presence in the specific type of vehicle;
- scenarios (S7, S8, S18, S19) - the user moves on a different type of vehicle than the one in which he or she was identified by the system (e.g., for S7 it was identified on the 174 line bus, but boarded a line 17 tram instead). The system is to deny the user's presence in the respective type of vehicle;
- scenarios (S4, S5, S6, S14, S15, S16, S17, S20, S21, S22, S23, S24, S25) - the user moves on foot, by bicycle or car, but was instead identified by the system as a passenger on a tram, bus, or train (e.g. for S4, the user was on foot, but was identified as a passenger on tram line 4). The system is to deny the user's presence in the respective type of vehicle;



1	Nr	Nazwa	Nr scenariusza	Scenariusz	Model_0_0_Walking	Model_0_1_Bus	Model_0_2_tram2	Model_0_2_Tram	Model_0_3_Train	Model	Model_0_5_Oth	Model_0_modelNum	Model_0_predicitonStart	Model_0_predicted
2378	24	S24	24	S24	5,41E-18	0	0,006823619	0,006823619	0,9931764	0	0	0	2019-04-01 14:36	[5.410565E-18, 1.01410
2379	24	S24	24	S24	2,77E-18	0	0,000625532	0,000625532	0,99937445	0	0	0	2019-04-01 14:37	[2.76965E-18, 1.268583
2380	24	S24	24	S24	3,68E-18	0	0,000442203	0,000442203	0,9995578	0	0	0	2019-04-01 14:37	[3.6815013E-18, 8.1633
2381	24	S24	24	S24	7,7E-19	0	0,000356215	0,000356215	0,9996438	0	0	0	2019-04-01 14:38	[7.705155E-19, 1.30224
2382	24	S24	24	S24	9,21556E-14	0	0,5931873	0,5931873	0,40681273	0	0	0	2019-04-01 14:38	[9.215555E-14, 2.47954
2383	24	S24	24	S24	0	0	0,000181719	0,000181719	0,99981827	0	0	0	2019-04-01 14:38	[4.210825E-21, 7.91494
2384	24	S24	24	S24	4,21E-18	0	0,000293017	0,000293017	0,9997069	0	0	0	2019-04-01 14:39	[4.20728E-18, 1.663963
2385	24	S24	24	S24	5,75104E-14	6,5E-19	0,9812603	0,9812603	0,018739657	0	0	0	2019-04-01 14:39	[5.751037E-14, 6.45135
2386	24	S24	24	S24	3,42E-18	0	0,016151713	0,016151713	0,9838483	0	0	0	2019-04-01 14:39	[3.4155164E-18, 4.6527
2387	24	S24	24	S24	1,1E-19	0	0,000513402	0,000513402	0,99948657	0	0	0	2019-04-01 14:40	[1.0916182E-19, 2.3800
2388	24	S24	24	S24	0	0	0,00011576	0,00011576	0,99988425	0	0	0	2019-04-01 14:40	[3.8952727E-21, 4.1670
2389	24	S24	24	S24	2,7E-19	0	0,000357111	0,000357111	0,99964285	0	0	0	2019-04-01 14:40	[2.730148E-19, 4.63335
2390	24	S24	24	S24	1E-20	0	9,47233E-05	9,47233E-05	0,9999052	0	0	0	2019-04-01 14:41	[1.0943394E-20, 4.1598
2391	24	S24	24	S24	0	0	0,000107747	0,000107747	0,99989223	0	0	0	2019-04-01 14:41	[2.6602197E-21, 2.2122
2392	24	S24	24	S24	0	0	5,14796E-05	5,14796E-05	0,9999485	0	0	0	2019-04-01 14:41	[8.582464E-23, 8.71167
2393	24	S24	24	S24	3E-19	0	4,32497E-06	4,32497E-06	0,9999957	0	0	0	2019-04-01 14:42	[3.0156477E-19, 4.0194
2394	24	S24	24	S24	2,76E-18	0	0,000313159	0,000313159	0,99968684	0	0	0	2019-04-01 14:42	[2.7646353E-18, 1.3226
2395	24	S24	24	S24	0	0	6,04504E-05	6,04504E-05	0,99993956	0	0	0	2019-04-01 14:42	[1.1013915E-21, 8.3853
2396	24	S24	24	S24	0	0	3,14302E-06	3,14302E-06	0,9999969	0	0	0	2019-04-01 14:43	[5.322486E-23, 2.44578
2397	24	S24	24	S24	1,732E-17	0	1,70975E-05	1,70975E-05	0,99998295	0	0	0	2019-04-01 14:43	[1.7324537E-17, 3.0741
2398	24	S24	24	S24	2,23982E-15	0	1,98879E-05	1,98879E-05	0,9999801	0	0	0	2019-04-01 14:43	[2.2398204E-15, 1.8202
2399	24	S24	24	S24	0	0	0,000342071	0,000342071	0,999658	0	0	0	2019-04-01 14:44	[1.5434523E-24, 9.4481
2400	24	S24	24	S24	8,1254E-16	0	0,000106389	0,000106389	0,99989355	0	0	0	2019-04-01 14:44	[8.125419E-16, 1.34705
2401	24	S24	24	S24	9,5036E-16	0	0,000596715	0,000596715	0,99940324	0	0	0	2019-04-01 14:44	[9.503579E-16, 8.80153
2402	24	S24	24	S24	7,76323E-12	2,54E-18	0,9964773	0,9964773	0,003522747	0	0	0	2019-04-01 14:45	[7.763225E-12, 2.54014
2403	24	S24	24	S24	1,87448E-13	0	0,26071063	0,26071063	0,73928934	0	0	0	2019-04-01 14:45	[1.8744782E-13, 6.2097
2404	24	S24	24	S24	8,55851E-15	0	0,013805669	0,013805669	0,98619425	0	0	0	2019-04-01 14:45	[8.558507E-15, 2.18921
2405	24	S24	24	S24	9,95122E-15	0	0,026134592	0,026134592	0,97386545	0	0	0	2019-04-01 14:46	[9.951216E-15, 3.79902
2406	24	S24	24	S24	4,02408E-14	0	0,0180944	0,0180944	0,9819056	0	0	0	2019-04-01 14:46	[4.0240834E-14, 1.9538
2407	24	S24	24	S24	2,40625E-14	0	0,00060845	0,00060845	0,99939156	0	0	0	2019-04-01 14:46	[2.406245E-14, 1.35372
2408	24	S24	24	S24	2,8896E-16	0	8,86764E-06	8,86764E-06	0,9999912	0	0	0	2019-04-01 14:47	[2.8895873E-16, 1.7392
2409	24	S24	24	S24	3,603E-16	0	2,59588E-06	2,59588E-06	0,9999974	0	0	0	2019-04-01 14:47	[3.6029685E-16, 8.6624
2410	24	S24	24	S24	1,36E-18	0	4,68407E-08	4,68407E-08	1	0	0	0	2019-04-01 14:47	[1.3587573E-18, 8.9965

Fig. 3. Sample test data sent to the central system by the BadApp4 application in test mode. Source: [authors' own elaboration]

As a result of the tests, over 2,400 test samples were investigated, which were sent to the central system using BadApp4 and converted into CSV format (the sample data is presented in Fig 3). The collected data is consistent with the scope of the integrated model (Tab. 1), and it also contains predictions made by the BadApp4 application for all types of vehicles (Tab. 3). During the analysis, a measure of recall, precision, and average F1-score were used to evaluate the model. After completing the tests, the acquired data was analyzed for six models by network 1 and network 2.

6. Results

Analysis of the collected data proved that for the network 1 model 4 it had the highest efficiency, which is at the level of 19% (as determined using F1-scope). The model correctly recognizes a user traveling by bus (Tab. 6) at a level of 40%. Other models recognized vehicle types with a much lower score, e.g., model 3 only achieved an average efficiency of 4% (Tab. 7).

Table 6. Result matrix network 1, model 4. Source: [authors' own elaboration].

	Walking	Bus	Tram	Train	Car	Bicycle
1-Walking	4	124	28	232	0	71
2-Bus	3	296	61	270	0	0
3-Tram	4	124	133	184	0	74
4-Train	0	17	3	103	0	0
5-Car	10	149	19	132	0	0
6-Bicycle	0	154	34	151	0	0

	precision	recall	f1-score	lueto
1	0.19	0.01	0.02	459
2	0.34	0.47	0.40	630
3	0.48	0.26	0.33	519
4	0.10	0.84	0.17	123
5	0.00	0.00	0.00	310
6	0.00	0.00	0.00	339
micro avg	0.23	0.23	0.23	2380
macro avg	0.18	0.26	0.15	2380
weighted avg	0.24	0.23	0.19	2380

Table 7. Result matrix network 1, model 3. Source: [authors' own elaboration].

	Walking	Bus	Tram	Train	Car	Bicycle
1-Walking	0	155	155	183	0	125
2-Bus	0	0	139	420	0	71
3-Tram	0	0	105	326	0	88
4-Train	0	0	50	82	0	0
5-Car	0	0	156	154	0	0
6-Bicycle	0	0	236	103	0	0

	precision	recall	f1-score	lueto
1	0.00	0.00	0.00	463
2	0.00	0.00	0.00	630
3	0.12	0.20	0.15	519
4	0.06	0.62	0.12	132
5	0.00	0.00	0.00	310
6	0.00	0.00	0.00	339
micro avg	0.08	0.08	0.08	2393
macro avg	0.03	0.14	0.05	2393
weighted avg	0.03	0.08	0.04	2393

Better results were obtained for the second network, which was trained on a larger set of training data (of 31 000 items, compared to 15 000). Average efficiency of 36% was recorded for the model 3A , compared to just 4% for the first network (an 8-fold increase in efficiency). The model can correctly recognize buses and trams (with 41% and 42%, respectively). Trains were recognized at a very low level of correctness - with only 5% of efficiency.

Table 10. Result matrix network 2, model 3A. Source: [authors' own elaboration]

	Walking	Bus	Tram	Train	Car	Bicycle
1-Walking	216	181	59	1	10	1
2-Bus	43	286	200	43	58	0
3-Tram	39	199	268	4	9	0
4-Train	10	48	58	6	8	2

5-Car	13	3	76	73	149	0
6-Bicycle	57	53	105	6	118	0

	precision	recall	f1-score	lueto
1	0.57	0.46	0.51	468
2	0.37	0.45	0.41	630
3	0.35	0.52	0.42	519
4	0.05	0.05	0.05	132
5	0.42	0.47	0.45	314
6	0.00	0.00	0.00	339
micro avg	0.39	0.39	0.39	2402
macro avg	0.29	0.33	0.30	2402
weighted avg	0.34	0.39	0.36	2402

The implementation of 23 scenarios using the 3A model returned 11 correct and 12 incorrect confirmations (Tab. 11).

Table 11. Model 3A relevance table for scenarios. Source: [authors' own elaboration]

ID	Scenario	Real means of transport	Detected means of transport (beacon)	Identified means of transport (system)	Calculated probability	Correct
1	S1	Tram	Tram	Bus	0,42121047	0
2	S2	Tram	Tram	Tram	0,5570947	1
3	S3	Tram	Tram	Tram	0,6546932	1
4	S4	Walking	Tram	Walking	0,73919785	1
5	S5	Walking	Tram	Bus	0,50425994	0
6	S6	Walking	Tram	Walking	0,42891294	1
7	S7	Tram	Bus	Bus	0,5332112	0
8	S8	Bus	Tram	Bus	0,514349	1
9	S9	Tram	Tram	Tram	0,50412667	1
10	S10	Bus	Bus	Bus	0,526391	1
11	S11	Bus	Bus	Bus	0,59002084	1
12	S12	Bus	Bus	Tram	0,39474916	0
13	S13	Train	Train	Tram	0,42402732	0
14	S14	Walking	Bus	Bus	0,84170413	0
15	S15	Walking	Bus	Bus	0,8163145	0
16	S16	Walking	Bus	Walking	0,7376452	1
17	S17	Walking	Train	Walking	0,61331165	1
18	S18	Bus	Train	Car	0,5281542	0
19	S19	Train	Bus	Bus	0,37173113	0
20	S20	Bicycle	Bus	Car	0,40750867	0
21	S21	Car	Bus	Train	0,41768146	0
22	S22	Walking	Brak danych	Car	0,36030892	0
23	S23	Car	Tram	Car	0,5133981	1

7. Conclusions

The implementation of the research described in the article allowed us to gather data that proved the first hypothesis. It allows us to assume that it is possible to build an integrated passenger identification model based on user behaviour models, vehicle routes, BeIn-BeOut activities and predefined relationships between data, which will allow for automation of fare collection and implementation of the "hands-free" and "pay-as-you-go " concept of fare. We proved that smartphone mobile devices with the BadApp4 research application installed enable automatic identification of the user as a vehicle passenger. The identification is effected by reading the signal of the vehicle's beacon transmitter and searching for it in the set of vehicle identifiers. This is how the Be-In event is carried out. Lack of signal causes the user to automatically stop being a passenger (Be-Out event). The time between events determines the period of use of transport services and gives the option of charging the fare in the "pay-as-you-go" model. It does not require any additional activities from the user because the device can be stored in a pocket or bag. This means that the concept of "hands-free" is also implemented. The implementation of the integrated passenger identification model in the BadApp4 research application and its tests allowed us to prove the possibility of reading, processing and sending, to the central system, of 47 elements belonging to 4 different data models. The feasibility of establishing and implementing connections between models has also been demonstrated. What proved to be the most difficult to establish is the correlation type relationship between the User Behavior and Vehicle Type models. It required developing and testing a forecasting mechanism designed for machine learning, and then transferring the mechanism to a mobile application.

Our earlier research, which is not covered by the present article and was conducted at the earlier stage of the project enabled us to formulate the thesis that the application of machine learning mechanisms allows the correct identification of the user as a passenger traveling on a specific type of vehicle. These studies have proven the effectiveness of identifying and correctly classifying travel at the level of 91%, whereas in extreme cases it reached 100%. However, the tests were conducted in laboratory conditions, on homogeneous data, and with a different data range. The research conducted in real-life conditions, on different range of non-homogeneous data, as presented in this article, did not confirm the following hypothesis resulting from the former thesis: Will the integrated passenger identification model using machine learning mechanisms allow for the correct identification of the user as a passenger travelling by a specific type of vehicle (bus, tram, train) at an accuracy level of above 90% in real-life conditions?

The lack of confirmation of this hypothesis may be the result of small amount of classified teaching data (there 31760 teaching samples in total, but e.g. for the bike there were only 649 samples available) and its low diversity (only 290 trips with sampling every 5 seconds). Expanding the training dataset may thus improve the quality of models. Sample quality should also be improved - whey were all collected during a relatively small number of trips; after removing the noise associated with the tester's failure to enter the all types of transport means required for data collection (network 2), we received 290 trips. Samples were taken at an interval of 5 seconds. In addition, the models differed from each other in the number of features (columns) that were taken into account during the research. The more columns, the more data was deleted during validation, due to missing entries in the respective columns. This led to a situation, where e.g. for the bicycle, that was already scarcely covered, only 24 samples remained for use in the most restrictive models. What's more, model 5 could not be tested, because the validation process resulted in a collection consisting of only 2 classes (bus and tram), additionally unevenly distributed with disproportionately high bus coverage. What is optimistic is the fact that we proved the high sensitivity of models to data growth. For example, for the third model, the first network saw an 8-fold increase in efficiency after doubling the teaching data volume.

Further research directions should include the analysis of applicability of other models. Due to the sequentiality of collected data over time, it seems appropriate to use models that allow their analysis. Therefore, the possibility of using recursive neural networks should also be considered. It must also be taken into account that statistical models are potentially better at smaller training trials than neural networks.

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