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Position Estimation in Mixed Indoor-Outdoor Environment Using Signals of Opportunity and Deep Learning Approach

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***Abstract*—To improve the user's localization estimation in indoor and outdoor environment a novel radiolocalization system using deep learning dedicated to work both in indoor and outdoor environment is proposed. It is based on the radio signatures using radio signals of opportunity from LTE an WiFi networks. The measurements of channel state estimators from LTE network and from WiFi network are taken by using the developed application. The user's position is calculated with a trained neural network system's models. Additionally the influence of various number of measurements from LTE and WiFi networks in the input vector on the positioning accuracy was examined. From the results it can be seen that using hybrid deep learning algorithm with a radio signatures method can result in localization error 24.3 m and 1.9 m lower comparing respectively to the GPS system and standalone deep learning algorithm with a radio signatures method in indoor environment. What is more, the combination of LTE and WiFi signals measurement in an input vector results in better indoor and outdoor as well as floor classification accuracy and less positioning error comparing to the input vector consisting measurements from only LTE network or from only WiFi network.**

***Keywords*—radiolocalization; deep neural network; hybrid localization**

I. Introduction

A DEMAND for indoor and outdoor localization systems is constantly growing due to the need of increasing people's safety and comfort. Indoor localization is used in order to localize and navigate users in shopping centers, hospitals or in underground parking lots [1], [2] and outdoor localization can be used to localize and navigate autonomous cars [3]. Undoubtedly, position estimation in both indoor and outdoor environment will be crucial in creating smart cities in the future. What is more, it is needed to use the already existing radiocommunication infrastructure for the localization system to be cheaper in implementation and more accessible.

Global Positioning System (GPS) which is a frequently used radiolocalization system nowadays is not accurate enough, especially in the indoor environments [1]–[4]. Satellite systems are vulnerable to multipath propagation, path loss, lack of line of sight (LOS) or signal scattering. It is especially noticeable in indoor environment making it nearly impossible in practical usage. Problems with the propagation of signals through the walls and ceilings cause that the position of the user is often indicated outside of the buildings. It is also completely impossible to determine the floor on which the users are located in the buildings.

There are localization methods that use measurements of a Received Signal Strength (RSS) from base stations (BS) of cellular networks or access points (AP) of Wireless Fidelity (WiFi) networks [2], [3], [5]. The biggest advantage of this approach is that it uses an already existing infrastructure, and what is important, in terms of WiFi an infrastructure created inside of buildings.

In this article the localization system based on the RSS measurements and a fingerprinting method [6], [7] is presented. What is more, proposed position estimation system is assisted with deep learning (DL) algorithms. Taking into account the non-linearity of localization process the demand for using DL algorithms and the number of research papers using DL algorithms in localization are rising [8], [9]. In the fingerprinting method it can be used in measurement phase [10], [11] or in localization estimation phase [12].

In existing research it is common to consider either indoor or outdoor localization separately with relatively small localization areas [12], [15]. Researchers also usually take measurements of only WiFi Received Signal Strength Indicator (RSSI) [8]–[10], [12], [16], [17]. Considering the current state of the literature, the mere use of deep learning is not an innovative solution. However, the developed comprehensive system that combines algorithms for the implementation of user radiolocation in both multifloor indoor and outdoor environments along with the detection of the environment in which it is located should be considered innovative in relation to the existing solutions. Additionally, measurement studies were carried out, which showed that the hybrid approach (using cellular networks and local WiFi networks data) allows to increase the accuracy of user's localization estimation in indoor environments.

Innovative radiolocation system described in this paper locates users in both indoor and outdoor environments and works on the basis of measurements from both Long Term Evolution (LTE) network and WiFi. Additionally it is supported with DL algorithms.

This work was developed within the statutory activity of the Department of Radiocommunication Systems and Networks, Faculty of Electronics, Telecommunication and Informatics, Gdansk University of Technology.

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The main contributions of the paper are:

- An innovative indoor and outdoor radiolocalization system that uses channel state estimators measurements from LTE and WiFi networks with DL algorithms was designed.
- A measurement software application that measures WiFi RSSI, LTE RSSI, LTE Reference Signal Receive Power (RSRP) and LTE Reference Signal Receive Quality (RSRQ) was created.
- With this application the measurements were carried out, fingerprinting database was generated and data sets were formed.
- Deep neural networks (DNN) were implemented. DNNs were given a vector of measurements data sets from one user and user's position was computed.
- The effectiveness of the developed localization system i.e. trained models of deep neural networks, was verified on the basis of the measurement campaigns.
- The results show that the hybrid approach of using signals from both LTE and WiFi network gives more accurate position estimation than using signal from only one network.

The rest of the paper is organized as follows — in Section II a discussion of the related work on the WiFi and LTE signal based positioning methods using DNN algorithms is presented. In Section III a proposed system prototype is described. Conducted measurement scenarios are presented in section IV. The result analysis of the proposed system is discussed in Section V and the summary of this paper is presented in Section VI.

II. Related works

Deep learning based localization using signals from LTE or WiFi networks has been already studied in the past. In this section different approaches from previous research were presented. Authors of those articles usually take into consideration only an indoor environment.

When using a radio signatures method the process of collecting measurements from a vast area can be time and memory consuming. In [10] authors created radio maps using deep gaussian process which describes a relation between RSS measurements and position in which the measurements were taken. Thanks to this approach they constructed a radio map using only 20% of measurements similar to the one constructed with 100% of measurements.

Using only measurements of WiFi RSS can result in small localization accuracy. To address this problem, a hybrid RSS and channel state information (CSI) system is proposed in [8], [12]. In [8] fingerprint database is made of RSS and CSI with a high correlation. Measurements from 28 reference points (RP) were collected in 16×8 m room. About 90% of localization errors is less than 1.5 m in this system. In [12] it has been found that DL using CSI signals achives better localization accuracy than DL using RSS signals. Convolution neural network (CNN) using CSI signals achieved maximal localization error of 0.92 m with probability of 99.97%.

Giving the non-linearility and complexity of position estimation using RSS signals researchers tend to implement a systems of different algorithms [16]–[18]. In [16] authors proposed a DL system integrating CNN, Siamese architecture and regression network. Proposed method achieved mean positioning error of 1.3 m in the 80×20 m area with the fast-moving user. In [17] system which includes DNN, CNN, Dempster-Schafter theory and AutoEncoder in the 14.4×7.2 m room achieved Root Mean Square Error (RMSE) of 1.5 m. In [18] authors used pedestrian dead reckoning with WiFi weighted path loss algorithm and linear Kalman filter. This system uses accelerometer, gyroscope and magnetometer sensors. With the path over a rectangular of size 29×45 m the maximum positioning error was 1.5 m.

In [19] authors decided to consider a heterogenous indoor localization system including measurements from both LTE and WiFi network. They also examined localization accuracy when using only the LTE signals or only the WiFi signals. In the localization area of two $3,5 \times 4,5$ m rooms the smallest RMSE localization error was 0.9 m for the combination of both networks.

In the table I a summary of already described in this chapter and other published articles in which authors proposed radiolocalization fingerprinting systems supported with DL algorithms is presented.

TABLE I
Summary of existing research about radiolocalization fingerprinting systems supported with DL algorithm

Article	Area size	Data sources	Algorithm	Performance
Indoor localization				
[8]	16×10 m	WiFi	DNN	90% errors less than 1.5 m
[9]	390×270 m	WiFi	DNN	5 m - max error
[10]	2300 m^2	WiFi	DNN	1.3 m - mean error
[12]	$13,82 \times 8,56$ m	WiFi	DNN, CNN	0.9 m - max error
[16]	80×20 m	WiFi	DNN, CNN	1.2 m - mean error
[17]	$14,4 \times 7,2$ m	WiFi	DNN, CNN	1.5 m - mean error
[19]	two $3,5 \times 4,5$ m rooms	WiFi, LTE	DNN	0.9 m - mean error
[20]	two 3000 $m^2 floors$	WiFi	Bayes filter, hidden Markov Model	1.9 m - mean error
[21]	10×10 m floors	WiFi	Weighted Fuzzy Matching, Kalman Filter	0.4 m - mean error
Outdoor localization				
[15]	60×60 m	WiFi, LTE	DNN	0.4 m - mean error
[22]	100×100 m	simulation RSS	DNN	5.5 m - mean error

From the analysis of existing research it can be concluded that there is a lack of system combining both indoor with multifloor classification and outdoor radiolocalization systems. It can be also noticed that there are not many papers in which authors designed a heterogeneous systems with measurements from both LTE and WiFi networks.

III. System prototype

The system created as part of this project aims to locate users in multifloor indoor and outdoor environments. Locating users is based on the deep learning algorithm. Due to the use of the fingerprinting method, it is necessary to collect measurements of channel state estimators from WiFi and LTE. Moreover, the system works on commercial available mobile phones. Therefore, the software implementation of the project assumes the creation of a measuring station in the form of an application for mobile phones with the Android system, used to obtain low-leveled channel state estimators from WiFi and LTE networks. No need to purchase additional specialized devices, only the use of the existing infrastructure of selected networks makes the construction of the system universal at the expense of less accurate measurements. A deep learning algorithm, specifically a feedforward neural network (FNN), was chosen as the locating algorithm. In the training phase of the neural network, a genetic algorithm was used, which is responsible for the determination of such hyperparameters defining the network architecture, for which the trained model obtains the lowest possible user's localization Root Mean Square Error. However, in the test phase, the collected vector of input data is processed by the selected trained network model.

A. Concept

Positioning system developed for the purpose of this paper requires only generally available mobile phones with Android system. As there is no need to use additional specialized devices, the use of the existing infrastructure of LTE and WiFi networks makes the construction of the system universal at the expense of less accurate measurements. The collected data is stored in a dedicated database on a Hypertext Transfer Protocol (HTTP) server. The second part of the radiolocation system is responsible for processing information about signals from the LTE cellular network and WiFi network, training and verification of deep neural networks and visualization of the estimated positions using the Python programming language and the QGIS program. After collecting the necessary information about the signals measured by the user's device, the system determines its localization. Described radiolocation system is presented in Fig. 1.

B. Android measurement application

Measurement application prototype was developed for mobile phone with Android system to collect information for positioning system and send it to the external server. According to the structure and stack of Android system there is a possibility to obtain information about radio signal derived from LTE and WiFi networks via Java. For this project authors used three Xiaomi Redmi Note 8 Pro smartphones. The specification is presented in Table II.

The object-oriented programming language Java 1.8 and the Android Studio 4.2 programming environment under the open-source license were used to implement all the functions of the measuring application. The application implements a method that periodically collect information about the signals received by the mobile phone, emitted by nearby LTE enhanced Node B (eNB), nearby WiFi AP and GPS satellites. Measurements from the GPS system were performed in order to compare the localization errors of the designed system with the existing reference radiolocation system. The obtained parameters update rate of 1 Hz was assumed on the basis of article [23]. Additionally, in accordance with the design assumptions, in order to identify and distinguish users and check their movement history, a unique identifier of user equipment and the current time stamp are obtained from the Android system. In the described measuring application, the functionality of saving the collected information locally in the devices' memory has also been implemented in order to protect against the loss of data sent via the Internet to the external server. Measurements can be performed in two modes: measurement performed for a specified period of time or measurements performed for an indefinite period of time until the user stops the application.

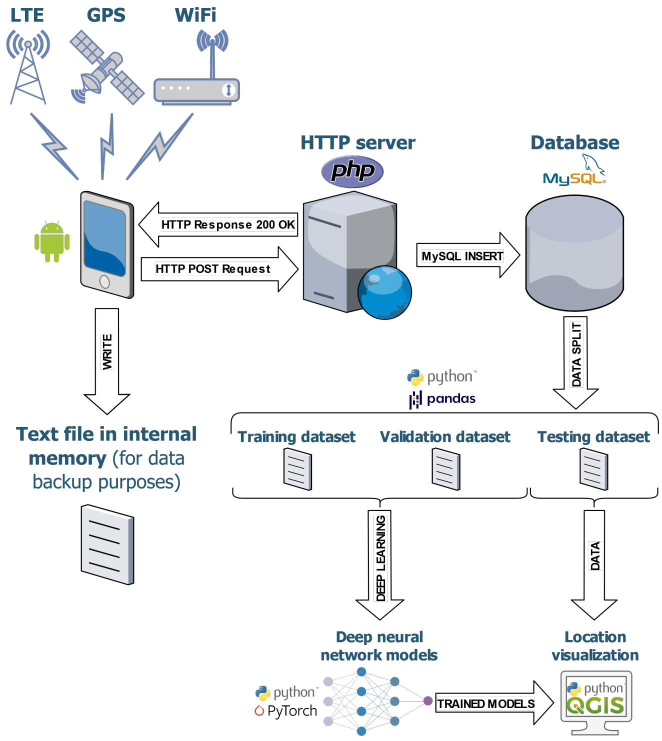

Fig. 1. Diagram of used components and their connections in the designed radiolocation system

TABLE II
USED SMARTPHONES

User	Android ver.	API level	Build number	Operator
1	11	30	RP1A.200720.011	Plus
2	10	29	QP1A.190711.020	T-Mobile
3	10	29	QP1A.190711.020	Orange

On the HTTP server side, incoming requests (POST) of the mobile application are directed to port 80 and handled by a script written in PHP language. The mobile application uses the Volley library for connecting the application with the server, creating requests to send the measurement data, creating listeners responsible for handling the 200 OK message and errors from the server. In addition, the PHP code on the server verify users and allow database to create new data records. One cycle of the processing and transmission loop of the measurement data set is completed upon receipt of the server feedback on the status of the operation performed.

It should be mentioned, that there are few limitations associated with Java programming language for Android and application layer of Android system. First of all, reffering to Android's documentation [26] there is a correlation between the version of Android installed on the mobile phone and available Java language methods. All used methods and fields are presented in Table III.

TABLE III
SUMMARY OF REQUIRED API FOR USED METHODS

Classes CellInfo, CellIdentityLte, CellSignalStrengthLte		
Method name	Min API level	Proper functioning on tested phone
getPci	17	Yes
getTimeStamp	17	Yes
getRsrp	26	Yes
getRsrq	26	Yes
getRssi	29	Yes/No
getCqi	26	No
getRssnr	26	No
Class ScanResult		
Field name	Min API level	Proper functioning on the phone
timestamp	17	Yes
frequency	1	Yes
SSID	1	Yes
BSSID	1	Yes
level	1	Yes
Class Location		
Method name	Min API level	Proper functioning on the phone
getLatitude	1	Yes
getLongitude	1	Yes
getAltitude	1	Yes

The analysis presented previously shows the following limitations in the designed radiolocation system for mobile phones with the Android system:

- API level versions consist of different lists of usable classes and methods, which excludes the use of e.g. getRssi method,
- the correct operation of the methods that can be used in Android Studio for each API level depends on the decisions of Android mobile phone manufacturers regarding the implementation of individual methods in their devices, e.g. the getCqi method, despite the availability for API level 29, does not function properly on mobile phone Xiaomi Redmi Note 8 Pro,
- it is not possible to implement the radiolocation system application on every Android mobile phone with correct operation guarantee.

C. Positioning method

Fingerprinting method assisted with DL algorithms consists of offline and online phase:

1) offline phase: during an offline phase the signal's measurements are taken in chosen reference points (RP). In this project it was decided to collect measurements of WiFi RSSI, LTE RSSI, LTE RSRP and LTE RSRQ. As a result with data preprocessing deep neural networks' input vectors are created. Input vectors with corresponding reference coordinates are then used to train neural network models.

2) online phase: testing data were collected in the online phase. The same measurements as in an offline phase are taken and with data preprocessing input vectors are created which are then processed by trained neural network model and an estimated user's position is calculated.

D. Data preprocessing

One of the goals of this paper is to examine an input vector configuration influence on position estimation. Therefore, vectors consisting of different number of measurements from WiFi and LTE networks were created. In case of not having enough measurements the gaps were filled with zeros [24].

For the outdoor scenario measured reference longitude and latitude were changed to the ECEF coordinates for RMSE calculation in meter unit.

In order to process data set in different ranges with neural network it is necessary to normalize it. It improves neural network calculations and decreases training error. It was decided to normalize our data by scaling it to a range of (0, 1) [25] with an equation (1):

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

where:
x_{norm} - normalized value
x - not normalized value
x_{min} - minimum value of data
x_{max} - maximum value of data

E. Deep learning

Given the non-linearity of position estimation based on the signals of opportunity a deep learning approach as localization algorithm was chosen.

1) Deep neural networks: The FNN was used as an example of simple deep neural network in order to simplify parallelization and implementation, which provides a low-computational final solution.

In order to obtain the smallest possible error in user localization, a hierarchical deep learning solution was developed (Fig. 4). In the context of user localization, in which indoor and outdoor localization were performed, the hierarchical neural network system developed in this project firstly determines whether the user is outside or inside the building. In case of an

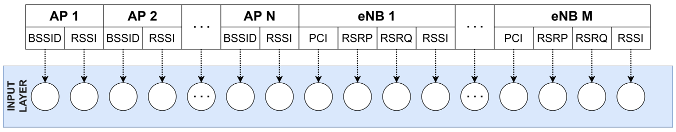

Fig. 2. Construction of the input vector of a deep neural network

outdoor classification data is passed to FNN model dedicated to position estimation in outdoor environment. On the other hand, if it has been assigned indoors, the classification of the floor on which the user is located takes place. Once the floor is designated, data is passed to FNN model dedicated to position estimation in indoor environment on given floor.

The number of hidden layers, the number of nodes in each hidden layer, the number of training epochs, the mini-batch size and the learning rate were selected using a genetic algorithm, which is described in detail in point 4. The Rectified Linear Unit (ReLU) activation function and the Adaptive Moment Estimation (ADAM) algorithm were used in the hidden layers in either regression (position estimation) and classification (floor estimation) networks. Additionally, in the output layers of regression networks as well as binary and multi classification networks, the linear, sigmoidal and softmax activation functions were used respectively. For classification networks the error function is the cross entropy function, while for regression networks the error function is the mean square error function.

The position estimation error obtained from regression network models is described by Mean Square Error (MSE) which is then computed into RMSE in order to obtain error value given in meters. The accuracy of the classification network models is determined by the percentages [0% - 100%].

Deep neural networks models were implemented with the use of programming language Python 3.9 and the library Pytorch 1.9. All models were trained and tested on a Windows 10 21H1 workstation with Ryzen 5 3600 CPU (6-core 3.59 GHz), 32 GB RAM, GTX 1660 Super (GPU) and 512 GB SSD in a Protolab laboratory of Gdańsk University of Technology.

2) Input vector structures: As mentioned earlier, based on the fingerprinting method, the input data vector for the neural networks consists of measured RSRP, RSRQ and RSSI values from LTE networks and RSSI from WIFI networks. In order to identify signal sources, dynamic MAC addresses of access points and local Physical Cell Identity (PCI) of eNB were used. Moreover, it was decided to investigate the effect of the number of selected signal sources on the localization accuracy while their order does not influence the accuracy of the system. Localization accuracy was also investigated using measurements only from WIFI or only from LTE. The structure of the input data vectors for configurations with N signal sources from WIFI and M signal sources from LTE is shown in fig. 2.

Reference vectors, which are necessary in supervised learning, have to be defined for both analyzed neural network model type (classification and regression). For the classifier network, the reference vector consists of a single number specifying the class for indoor and outdoor environment classification or for floor classification. For the outdoor regression, the reference data are the longitude and latitude converted to ECEF system coordinates. For the indoor regression, the reference data are the x, y local coordinates which can be mapped using anchor reference point to global system coordinates in ECEF.

3) Supervised learning: The processed input data is then divided into training, validation and test parts in a ratio of 60:20:20. The training and validation process continues for a predetermined number of iterations or until an interruption condition is met. In the design, the network training is interrupted if during the next 30 iterations the validation RMSE increases or the difference between the training and validation error is greater than a predetermined threshold of 1 cm (for indoor environment) and 50 cm (for outdoor environment) and during the next 30 iterations the validation RMSE does not decrease. This is necessary to avoid overtraining the network as well as to reduce the training time when smaller training error values are not achieved. Importantly, training is interrupted and the saved neural network model is the stored model from before the 30 iterations countdown began.

4) Hyperparameters tuning: The effectiveness of deep neural networks operation depends on many factors, including architecture hyperparameters or noise of the data provided to the input layer. The selection of hyperparameters of deep neural networks can be performed e.g. by grid search algorithm, random search algorithm or genetic algorithm [27], [28]. In this project, authors decided to implement a genetic algorithm in order to search a limited set of values of the tested hyperparameters for the optimal model architectures for each of measurement scenarios. Table IV present ranges of values of all tested hyperparameters.

TABLE IV
RANGES OF THE TESTED HYPERPARAMETERS

Hyperparameter	values range for classification	values range for regression
Number of hidden layers	{1, 2, 3, 4, 5, 6}	
Number of nodes	{10, 20, 30, ..., 400}	
Number of epochs	{10, 11, 12, ..., 100}	max 500
Batch size	{32, 64, 128, 256, 512}	
Learning rate	{1e-5,5e-5,1e-4,5e-4,1e-3,5e-3,1e-2,5e-2,1e-1}	

The presented ranges were selected based on the research described in [28]. The ranges of values of hyperparameters vary and similar effectiveness of the network operation can be achieved for extremely divergent values of the hyperparameters. The selection of a wide range of hyperparameter values for the grid search algorithm and the random search algorithm will allow to increase the number of possible solutions giving similar network efficiency results. However, such a choice will increase algorithm's operating time. According to the literature and conducted research, the use of a genetic algorithm allows an effective search for a multidimensional set of hyperparameters [28]. This results in a reduction of the time needed to find the optimal combination of hyperparameters.

In order to function properly, the genetic algorithm requires the determination of the conditions for interrupting its operation. There are many methods and approaches used in the literature [28], [32], however, in the implementation of this project, two mechanisms of stopping the genetic algorithm were used:

- when a certain number of generations of solutions were exceeded,
- when the most effective solution of a given population reaches a certain threshold of the accuracy of the classification or the accuracy of the localization estimate.

In this project it was established that the limit value of the iteration of the genetic algorithm generations will be 10, although other values are also used in scientific works, e.g. 5 [32]. It is worth emphasizing that this number may directly affect the results of the searched hyperparameter space. Consequently, a small number of iterations may not lead to finding the optimal solution. On the other hand, too many iterations can significantly increase the working time of the algorithm by searching the multidimensional space of hyperparameters more accurately. For each tested measurement scenario a threshold was defined upon reaching which the genetic algorithm would be interrupted. The threshold values have been determined on the basis of scientific research conducted in the field of radiolocation and the results achieved, summarized in Table I. In order to interrupt the work of the genetic algorithm at the right moment, i.e. taking into account the computational complexity and the result in the form of the most effective architecture found, the method of comparing the effectiveness between successive models of deep neural networks should also be used. Small differences in values, e.g. the RMSE between the best models after several iterations of the genetic algorithm may indicate the lack of new, better solutions on the examined plane.

A block diagram of a genetic algorithm implemented for the purposes of this project, supporting the selection of hyperparameters of deep neural networks is shown in Fig. 3. The genetic algorithm developed for this project is limited by a maximum number of 10 iterations, and each population consists of 20 individuals, i.e. solutions. Each individual of the population is a set of values of the examined hyperparameters. The algorithm begins by uniform randomizing the initial population of deep neural network architectures. On the basis of all models training of a given population, the models are sorted according to the results of the achieved work efficiency. Then, the best 10 models by means of minimizing RMSE are selected that will be involved in further processes of the genetic algorithm. The most effective models from the previous population from sequence number 2 to 10 are involved in the mutation process. It was decided that with a probability of 0.05 [28] each model would be able to be mutated with an equal probability of one of the 5 hyperparameters (in the case of classification) and one of the 4 hyperparameters (in the case of regression). The mutation process was carried out by drawing a new value of a given hyperparameter from the range constituting +/- 10% of the entire specified range of values in relation to the last value of a given hyperaparameter [28]. The value of 10% will allow a more detailed examination of the searched space, verify the effectiveness of the individual's

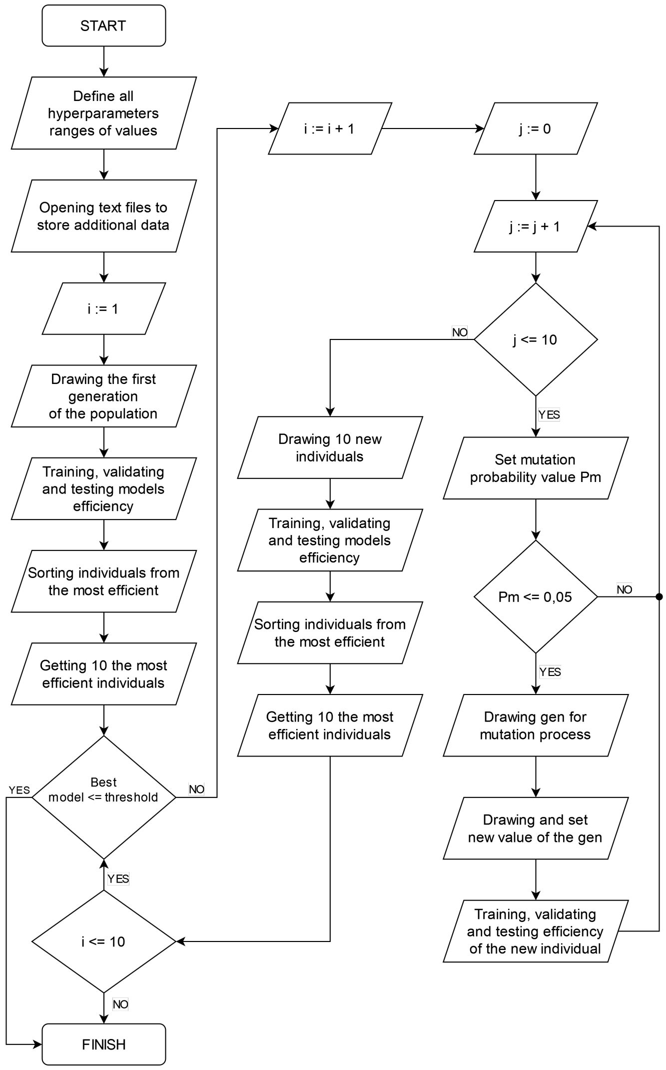

Fig. 3. Block diagram of used genetic algorithm

operation, i.e. architecture with a modified gene value, and assess whether the introduced change was beneficial.

F. System architecture

The hierarchical approach requires the interconnection of individual neural networks, with the output of one network indicating which network will be used in the next step. A functional block diagram of the created neural network system is shown in Fig. 4.

Each of the deep neural networks that make up the hierarchical approach described previously consists of an input layer, n hidden layers and an output layer with the number of output elements in the vector depending on the network model.

IV. SCENARIOS

The purpose of the proposed deep learning system is to locate users inside and outside of the buildings. It is therefore necessary to carry out measurements in both of these environments. In outdoor environment only one static scenario was defined, while in indoor environment four static scenarios

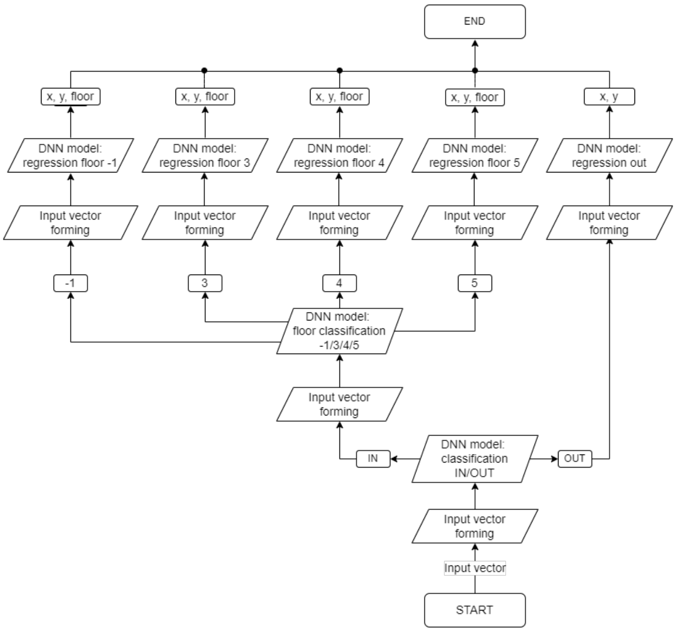

Fig. 4. Network of connected classification and regression DNN models

were defined. For each of the static scenarios there was corresponding dynamic scenarios. 1077647 data records of WiFi's information and 70081 data records of LTE's information were gathered in both offline and online phases.

Due to the lack of information on the localizations of nearby WiFi access points, cellular networks base stations and information on propagation loss, which also are used for estimating UE localizations [29], the method of creating a radio map with the use of radio signatures was selected. The localization process using RSS parameter is divided into two phases: the offline phase (static scenarios) and the online phase (dynamic scenarios). In the offline phase, a radio map with reference points (user's positions) was created, while in the online phase the effectiveness of the tested localization algorithms was estimated. For this reason, separate measurement scenarios for both of the mentioned phases were distinguished. Three mobile devices were held by the users at a height of 100-120 cm above the ground in a gesture representing the use of the device.

Measurements for the training set in the offline phase were taken for one minute at each reference point, with all of the single measurement data sets being gathered every 0.5 seconds. The three users were in a static position - standing motionless with the UE in front of them. In order to test the designed radiolocation system in the online phase the testing route was covered by three users at a walking pace without stopping at individual reference points.

A. Outdoor scenario

The studied environment in the described scenario is the area of the campus of the Gdańsk University of Technology, where a 1760 m long route was marked out. The first (starting) point in the easternmost area of the campus. The end point was located in front of the main entrance to the building A of the

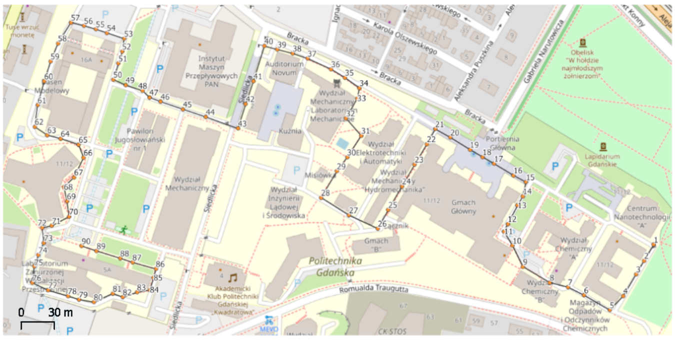

Fig. 5. Outdoor measurement scenarios

Faculty of Electronics, Telecommunications and Informatics. The measurement route runs through the campus area of the university due to the need of investigation the effectiveness of the localization algorithm in various propagation conditions, i.e. corresponding to the canyon streets environment, half-open area, and LOS/Non LOS situations according to the base station localizations around the campus. It is also worth noting that the positions of LTE base stations and WiFi access points were not known a priori.

In the offline phase a radio map was created. The proposed online phase route (gray line) with 90 reference points (orange points) of the offline phase marked on it is presented in Fig. 5. The distance between nearest reference points vary from 10 to 30 meters due to the need to conduct the measurement campaign as accurately as possible. RPs were situated in the so-called characteristic places. This resulted in decreasing the values of possible errors caused by the wrong mapping of the actual reference points positions on the map from which values such as latitude and longitude were gathered. Furthermore, according to [30] there is a visible connection between the density of data position used for training data sets and the efficiency of deep learning algorithm, where the value should be equal to 4.5-6.5% of the distance between base station or 2.3-3.3% of the measurement area. Unfortunately, in the first case the positions of neither WiFi's APs nor LTE's eNBs were known. Nevertheless, area distance of the wider axis is approximately equal to 680 m, where these 2.3-3.3% gives the distances around 15-22 m.

B. Indoor scenarios

All indoor scenarios measurements were carried out inside of the building A of the Faculty of Electronics, Telecommunications and Informatics (ETI A) of the Gdańsk University of Technology. A reference point of the local coordinate system has been established for each of the distinguished floors. Measurements from each of the floors were additionally marked with the floor number on which they were carried out. Similarly, as in the outdoor scenario, there was information about the received signals from WiFi, GPS and cellular networks as well as additional user information in one set of measurement data.

The research [30] on the impact of forming learning datasets on the effectiveness of deep learning in radiolocation appli-

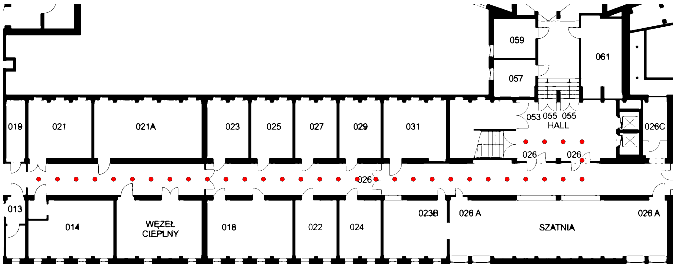

Fig. 6. Radio map for indoor scenario II A

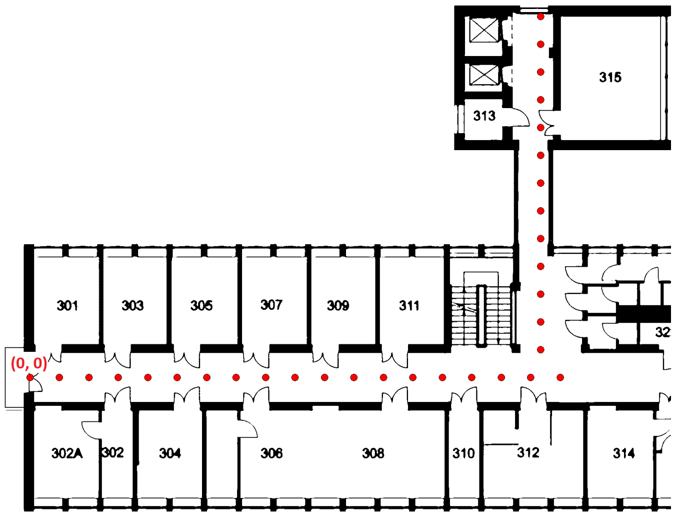

Fig. 7. Radio map for indoor scenarios II B, II C and II D

cations shows that the positions of nearby reference points should be set with constant distance intervals. The RPs' grid distance was also examined in [33]. Thus, a constant distance value between adjacent RPs of the created radio map was used. A systematic review of the literature shows that for the indoor environment the discussed value vary from about 1 m to 2 m [12], [16], [17], [31]. For the studied case the need to obtain a high UE position localizations accuracy, it was decided to use the mean value of the distance between nearby reference points equal to 1.5 m. This value was the same for all of the indoor scenarios.

In the indoor environment, several measurement scenarios have been distinguished, depending on the measurement conditions and the localization of measurement points. Scenario II A focuses on the environment with poor propagation properties - the basement of the ETI A building. This scenario has the highest number of reference points among the indoor scenarios. Next indoor scenarios are scenarios II B, II C and II D, where the offline phase RPs and the testing route of the online phase look the same. However, mentioned scenarios differ by the floor number on which measurements were taken. In Fig. 6 and Fig. 7 radio maps of the offline phase are presented, respectively for the scenario carried out in the basement (II A) and the scenarios carried out on floors: 3, 4 and 5 (II B, II C, II D).

V. Results

This chapter of the paper is intended to present the results of the measurement application, genetic algorithm and deep neural networks in the designed radiolocation system. The wide scope of the performed research will allow to determine the capabilities of the prototype system in terms of time resolution and possible accuracy of users' localization estimation in the described measurement scenarios. At the beginning, the ability of a UE to retrieve information about received signals via a mobile phone was presented. Then, the results of research on various structures of input vectors were presented, using the most effective architectures of neural network models obtained from the genetic algorithm.

A. Measurement application results

Before commencing the process of acquiring information about the radio signals received by the user's device for the designed radiolocation system, a series of test measurements was performed. The purpose was to empirically confirm the choice of selected time of radio signals indicators refreshing. The times between new information about radio signals that can be read by the Android application layer are summarized in Table V.

TABLE V
Time results of test measurements for outdoor scenario

WiFi scanning throttle limits turn on (default option)	
Min refreshing time	1.7s
Avg refreshing time	20s
Max refreshing time	89.4s
WiFi scanning throttle limits turn off	
Min refreshing time	1.1s
Avg refreshing time	2s
Max refreshing time	6.3s
LTE	
Min refreshing time	5s
Avg refreshing time	5.9s
Max refreshing time	27.7s
Selected time resolution of online measurement phase	1s

It was found that the average time of refreshing information about signals from the WiFi network is about 20 seconds (for the user using the default Android settings), and for the LTE network it is about 6 seconds. This means that the sufficient average time to create the input vector to the deep neural network will not be shorter than the average time to obtain new information about signals from the LTE or WiFi network.

In Figures 8, 9 and 10 the time dependencies between successive updates of information on received signals from the LTE network, WiFi network and the GPS system are shown. It has been noticed that depending on the environment in which the measurements are performed, the time between reading the information about signals from the LTE network received by mobile phones available to the programmer is variable. This time for each scenario is greater than or equal

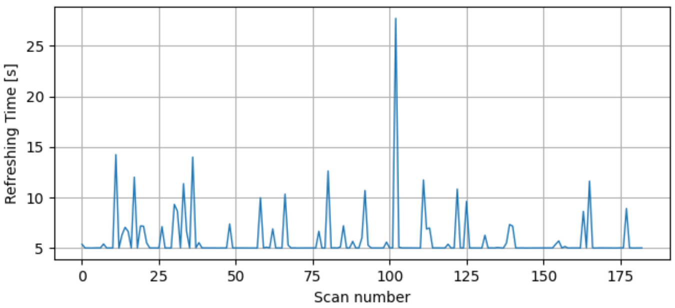

Fig. 8. The time between successive scans of information of received signals from the LTE eNBs

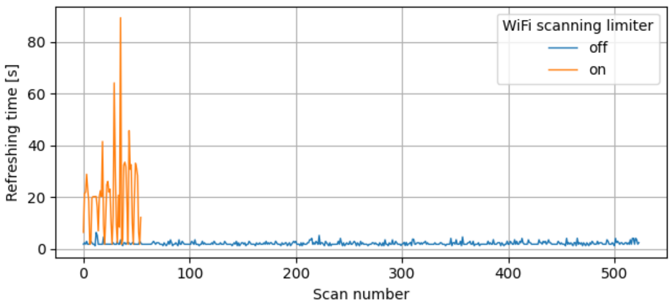

Fig. 9. The time between successive scans of information of received signals from the WiFi APs

to about 5 seconds. A dispersion of the refreshing time was noticed even on the adjacent floors of the Faculty of ETI A building. Table V and Fig. 9 present the test results related to the limitations of the Android system. According to the documentation available for Android application developers, it follows that the limitations related to the increase in the interval between the available new information about signals from cellular networks and WiFi networks are dictated by the energy saving process of mobile phones. Disabling the default setting in the developer options for limiting WiFi network scanning reduces the average waiting time (from about 20 s to 2 s) for a new WiFi network information scan made by mobile phones in the expense of energy saving process. The average time of updating the user's position from the GPS system that can be obtained by the measurement application is about 2 s. Summing up the considerations - in the designed

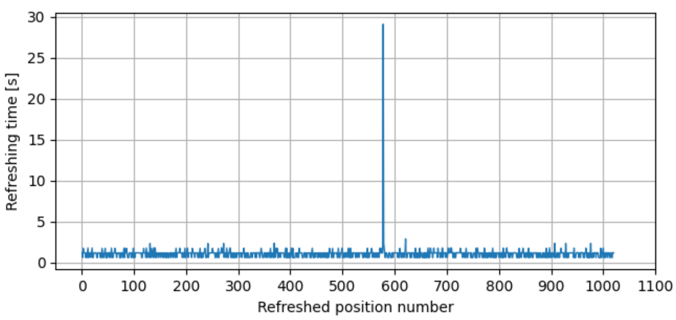

Fig. 10. The time between successive estimated user's localizations

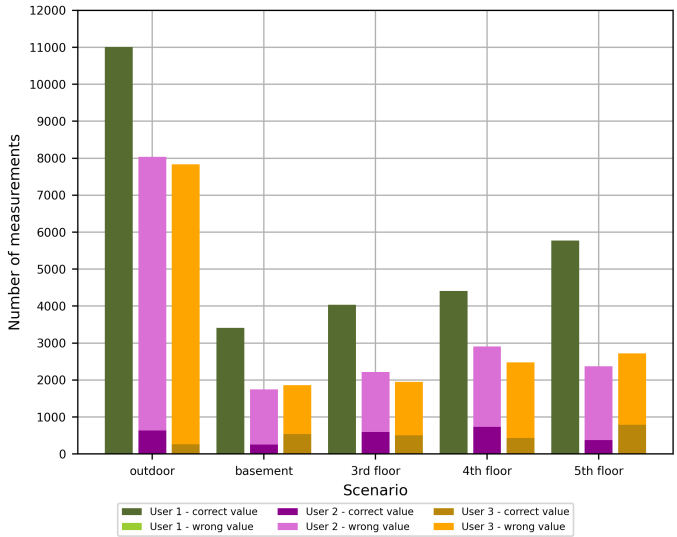

Fig. 11. Correct and incorrect measurements of the RSSI of the LTE eNBs

radiolocation system it is not possible to obtain a higher time resolution for receiving the position update than in the GPS localization system.

In Fig. 11 the discrepancy between the number of measurements received by user 1 (U1), user 2 (U2) and user 3 (U3) is shown. The number of measurements taken by the U1 is greater for the presented scenarios from about 27% to even about 50%. It should be mentioned here that the working time of the UE, and thus the acquisition time of measurement sets containing information about radio signals in each of the measurement scenarios, was the same for the three devices. Furthermore, the U1 device has recorded a valid measurement of the RSSI parameter in each read measurement data set. It can be concluded that the implementation of a radiolocation system based on the radio signature method for devices with Android system depends not only on the brand and model of the device, which was presented in the theoretical introduction in this documentation, but also on the version of the Android system on a given device. It has been confirmed that the use of identical methods provided in different versions of the API may cause a different result, which may directly translate into the effectiveness of the prototype radiolocation system due to the missing actual values in the input vector of the neural network.

B. Statistical Analysis of the Received Radio Signals

1) Relationship between scenarios and most common number of PCI/BSSID appearances in input vectors: To create the input vector of the deep neural network data, the number and the power of measured signals at a given reference point are important. Most frequently occurring numbers of BSSID and PCI addresses in the input vectors of the basement, 3rd floor, 4th floor, 5th floor and outdoor measurement scenarios, respectively are shown in table VI. It was observed that in the case of WiFi networks, the most frequent number of BSSID addresses in the input vectors is 16. Only in the indoor scenario of the basement floor, the input vectors most often consisted

TABLE VI
MOST COMMON NUMBER OF LTE AND WIFI ADDRESSES' APPEARANCES IN INPUT VECTORS

	PCI	BSSID
Indoor basement	2	14
Indoor 3rd floor	2	16
Indoor 4th floor	3	16
Indoor 5th floor	3	16
Outdoor	1	16

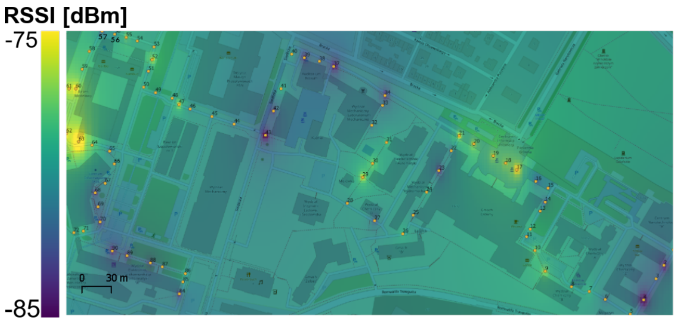

Fig. 12. Interpolated average RSSI power distribution for one user and one BSSID address - Inverse Distance Weighting Interpolation

of 14 BSSID addresses. In the case of cellular networks, the number of PCI addresses most frequently found in the input data vector is not so clear-cut. In the input vectors of the outdoor scenario, 1 PCI address was the most common, in the data obtained from the indoor scenarios on the basement floor and the 3rd floor most often there were 2 PCI addresses, while on the 4th and 5th floors, the most frequent number of PCI addresses was the number 3. Statistics of the frequency of occurrence of a given number PCI and BSSID addresses in the input vectors of deep neural networks are important from the perspective of the relationship between the selection of their appropriate combination and the effectiveness of deep neural networks.

2) Interpolated power distribution of the received signals: In order to present the maps of the interpolated power distribution of the received signals, it was decided to select the data obtained for one BSSID / PCI address by one user. The set of data needed to visualize the signal power distribution in

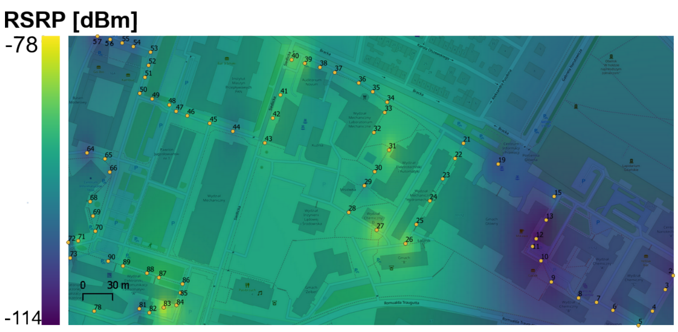

Fig. 13. Interpolated average RSRP power distribution for one user and one PCI address - Inverse Distance Weighting Interpolation

the outdoor scenario was selected on the basis of the largest number of occurrences of a given address of obtained data for one user and the greatest possible number of its occurrences at various measurement points. An example of the distribution of average RSSI and RSRP for data sets for one user and one BSSID and PCI address is shown in the figures 12 and 13.

From the visualization of interpolated power distribution maps, it can be observed that the values of the measured powers differ significantly depending on the place of measurement. Power values vary from -90 dBm to -60 dBm for RSSI and from -112 dBm to -82 dBm for RSRP, nevertheless the power ranges on maps were chosen empirically to ensure better visualization. The strength of the received signals may be influenced by factors such as the topography, LOS/NLOS and the user's distance from base stations and access points.

C. Selection of DNN hyperparameters

To test the effectiveness of the neural network models, the input vector structure was used, consisting of information from ten WiFi access points and three eNBs of the LTE network. The results of the best architectures found after 10 iterations of the genetic algorithm for each measurement scenario are shown in the following tables VII and VIII.

TABLE VII
RESULTS OF GENETIC ALGORITHM FOR CLASSIFICATION

	Indoor-Outdoor Classification	Floor Classification
Iteration of Genetic Algorithm	2	6
Number of Hidden Layers	3	5
Number of Nodes	355	250
Batch size	256	128
Learning Rate	0.001	0.0005
Training Acc	99.9%	99.3%
Validation Acc	99.7%	97.1%
Testing Acc	99.6%	96.7%

The efficiency of indoor and outdoor environment classification is higher than the indoor floor classification by approximately 3%. The efficiency of classification is a limitation of the designed system. In the case of a wrong indoor-outdoor or floor classification, the results of the position estimation in the coordinate system will not be reliable. System obtained similar floor classification accuracy as in existing articles e.g. 97% and 98% [13], [14].

The accuracy of the estimation of the localization of users on the floors does not differ significantly (0.3 m between the 3rd and 4th and between the 3rd and 5th floors), and the greatest similarity of the obtained efficiency results occurs between the 4th and 5th floor. Indoor results are decent because RMSE values are smaller than the distance between the measurements points. The largest RMSE error in the user's localization estimate was obtained for the outdoor scenario and it was 15m for a network structure with 4 hidden layers and 169 nodes in each layer. In general, the structures of the best architectures for the regression problem are similar. In conclusion the number of hidden layers should be in a range

TABLE VIII
RESULTS OF GENETIC ALGORITHM FOR REGRESSION

	Basement	3rd Floor	4th Floor	5th Floor	Outdoor
Iteration of Genetic Algorithm	1	7	10	9	2
Number of Hidden Layers	2	5	3	3	4
Number of Nodes	311	213	247	239	169
Batch size	64	32	32	128	32
Learning Rate	0.001	0.001	0.001	0.001	0.0005
Training RMSE	0.5 m	0.3 m	0.4 m	0.4 m	6.8 m
Validation RMSE	2 m	0.7 m	1 m	1 m	15.9 m
Testing RMSE	1.5 m	0.7 m	1.1 m	1.1 m	15 m

of 3 to 5 and the number of nudes should be greater than 200 for indoor environment.

D. Radiolocation system results

On the basis of the most effective architectures selected from the previous chapter, in this article the authors examined the influence of the content and structure of input vectors of deep neural networks. Figures 14, 15 and 16 show the results obtained by the best models trained on various m WiFi and n LTE input vector configurations, where m is the number of measurements from the WiFi network and n is the number of measurements from the LTE network in the input vector.

1) Classification error: The results of classification accuracy for the indoor and outdoor classification as well as the floor classification are presented in the Fig. 14. The highest classification accuracy for both scenarios were obtained using models trained on the vectors consisting of a combination of WiFi and LTE measurements. Changing the input vector in the floor classification of the indoor scenario has greater effect than in the indoor and outdoor classification. Different number of used WiFi signal indicators in the input vector of the indoor and outdoor classification causes approximately about 0,4% accuracy difference. However, there is a significant reduction in classification accuracy to 79% using signals indicators from 5 AP and to 76.3% using signal indicator from 1 eNB. The difference of 20,3% in accuracy shows that for the floor classification the number of used signals indicators in the input layer has enormous impact.

2) Positioning error: The results of RMSE error of user's localization in the indoor and outdoor scenarios are presented in the Fig. 15, 16.

The results obtained by the models trained on the vectors consisting of WiFi measurements or a combination of WiFi and LTE measurements reached the smallest RMSE localization errors for regression. For the indoor regression on floors 3rd, 4th, 5th, basement and the outdoor regression the differences between the largest and smallest RMSE localization

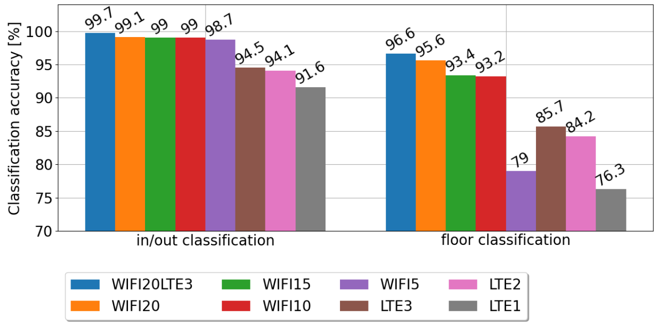

Fig. 14. Accuracy of classification of indoor and outdoor scenarios for the most effective architecture for various input vector structures

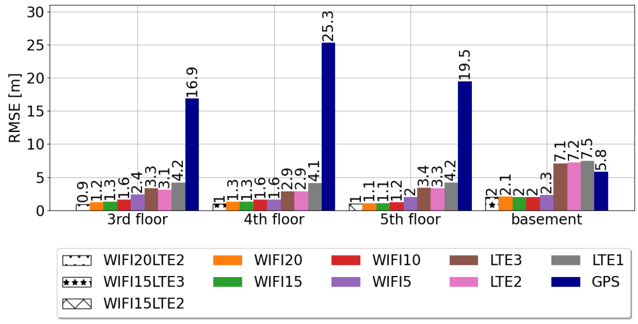

Fig. 15. RMSE error of user's localizations in the indoor scenarios for the most effective architectures for various input vector structures

error obtained by the given vectors are 1.5 m, 0.6 m, 1 m, 0.3 m and 19.1 m, respectively. The smallest localization RMSE errors for each scenario were obtained using models trained on vectors consisting of a combination of WiFi and LTE measurements. The lowest RMSE error of 0.9 m of user's localization was obtained for the indoor scenario on the third floor.

From the visualization of the users' localization estimates by the deep learning algorithm presented in Figure 17, 18, 19 and 20 it can be observed that the number of determined position estimates is smaller than the number of positions

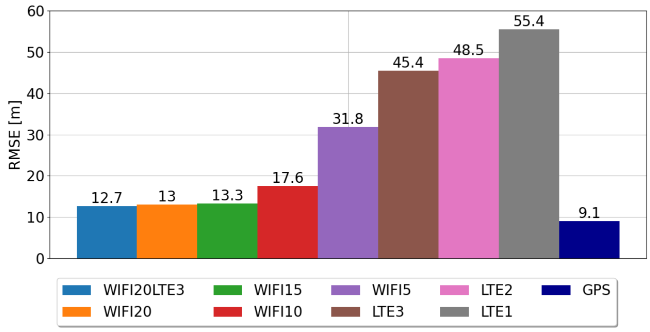

Fig. 16. RMSE error of user's localizations in the outdoor scenario for the most effective architectures for various input vector structures

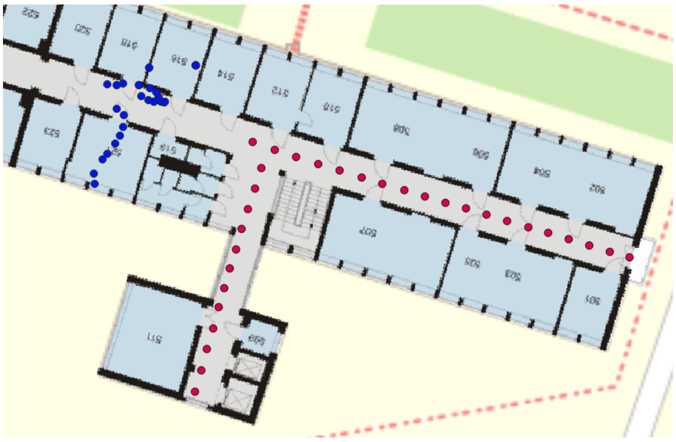

Fig. 17. Map of GPS route points (blue colour)

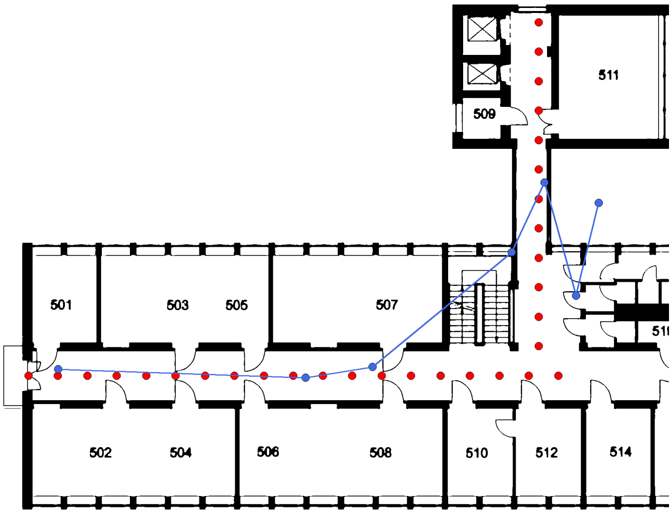

Fig. 18. Map of route points estimated by deep neural network models for the 'LTE2' input vector (blue colour)

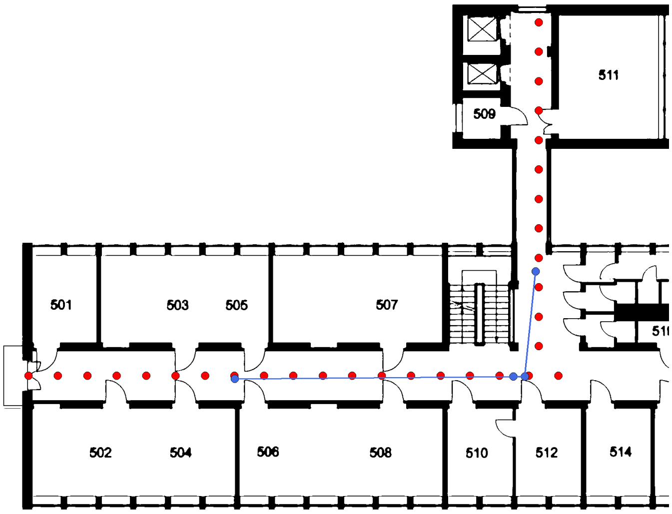

Fig. 19. Map of route points estimated by deep neural network models for the 'WiFI15' input vector (blue colour)

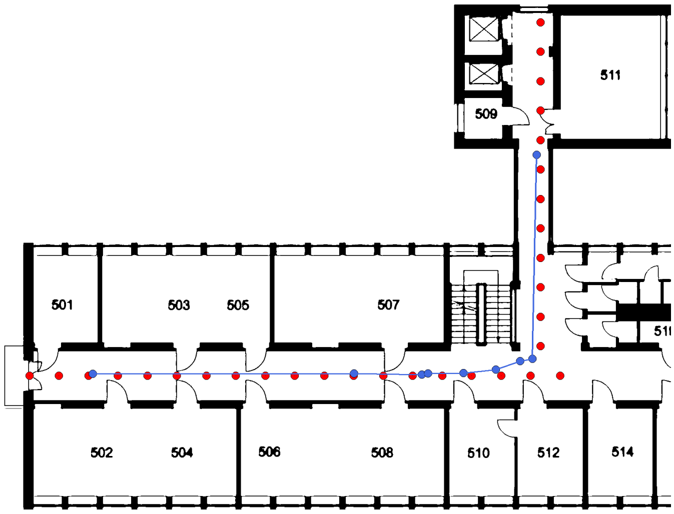

Fig. 20. Map of route points estimated by deep neural network models for the 'WiFi15LTE2' input vector (blue colour)

determined by the GPS system. It can be seen that the density of points representing the estimated localization of users is different in relation to the input vectors containing separately information about signals from these networks. This results in the advantage of the classic GPS localization system over the method developed by the authors of this article, based on radio signals from WiFi and LTE networks. In the case of the GPS system, the assumption described in the theoretical introduction is confirmed that the GPS system provides greater measurement time resolution. The presented results of the localization accuracy confirmed as expected the effectiveness and usefulness of the proposed deep learning system over the GPS system in the indoor scenario. Furthermore, it can be concluded that the signals of the hybrid WiFi and LTE networks significantly (up to 5.5 m in the basement indoor scenario) contribute to increasing the accuracy of the users' localization estimates. The difference in accuracy in the indoor scenario is from 3.8 m to 16 m, which is a significant increase in the accuracy of the localization compared to the GPS system regarding usage of only WiFi or only LTE signals indicators. Only in the outdoor scenario, the GPS system works more efficiently, achieving a 3.6 meters lower average localization error. However, it is known that even the GPS system, especially in the conditions of dense urban environment, may be characterized by an increase in errors, and the use of signals of opportunity would allow, e.g. to maintain localization services. On the third floor, the highest accuracy of position estimation was obtained. Those results are comparable to the accuracy of determining the place of reference measurements. Therefore further improvement of the accuracy of position estimation requires, e.g. automation of the measuring process or the use of a reference location system with an error of at least one order of magnitude lower.

VI. Conclusion

In this paper radiolocation system prototype based on signals of opportunity with the use of deep neural networks was presented. It has been shown that the use of input vectors consisting of the parameters of WiFi and LTE signals gives greater accuracy of users' position estimation than those consisting of only WiFi parameters or only LTE parameters. On the basis of the obtained results, it can be concluded that:

- the correct functioning of the prototype radiolocation system largely depends on the user's UE type and the version of the operating system,
- the most effective solutions - architectures of deep neural networks obtained by the genetic algorithm - do not differ from each other in terms of the obtained accuracy of system, and the range of hyperparameters for which similar values of effectiveness are obtained is wide (number of hidden layers from 2 to 5, number of nodes from 169 to 311, batch size from 32 to 128 and learning rate from 0.0005 to 0.001),
- the use of a combination of measurements from WiFi and LTE networks allows for a more accurate localization of users in a radiolocation system based on the deep learning method compared to using measurements only from the WiFi network or only from the LTE network,
- user's localization determined by the designed radiolocation system, using the deep learning algorithm, have RMSE error lower of even 24.3 m (in case of standalone GPS) than the localization of users designated by standalone GPS, WiFi and LTE systems in an indoor environment. Thus, localization services used e.g. to monitor people using the existing infrastructure can be provided,
- the effectiveness of such a comprehensive system depends on the effectiveness of the classification of the propagation environment, which, thanks to deep learning, was achieved with the accuracy of 99.7% for indoor-outdoor classification and 96.6% for floor classification,
- the prototype of the proposed radiolocation system based on the measurements of radio signals is characterized by a lower time resolution compared to the classic GPS localization system due to the commercial UE limitations.

In the future works searching for the most effective combination of information of received signals by UE's with the use of filtration can be performed. It is necessary to increase the number of measurements in various environments and in different geometries of the localization of reference stations in the localized area, to conduct research on the impact of the density of reference point implementation on the effectiveness of the localization system based on deep learning.

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