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Artificial Intelligence-Based Classification of Multipath Types for Vehicular Localization in Dense Environments

Yaser A. Bakhuraisa[1], Azlan B. Abd Aziz[1]*, Tan K. Geok[1] , Azwan Mahmoud[1], Aminuddin A. Kayani[2], Noor Maizura[3]

[1] *Faculty of Engineering, Multimedia University (MMU), Meleka, 75450, MALAYSIA*
[2] *Functional of Information and Microsystems Research Group, RMIT University, Melbourne, 2476, AUSTRALIA*
[3] *School of Informatics and Applied Mathematics, University Malaysia Terengganu, Kuala Terengganu, 21030, MALAYSIA*

*Corresponding Author: azlan.abdaziz@mmu.edu.my
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Abstract

Multipath-geometry is a promising approach for vehicular localization in line of sight (LOS) and non-line of sight (NLOS) scenarios. In this approach, identifying the type of the propagated multipath components (MPCs) is an important preliminary stage. However, identifying the type of the MPC in dense multipath environments is challenging. The previous works proposed iterative methods for this task. These iterative methods have their limitations such as required more in-depth analysis and high complexity of computation. However, by leveraging artificial intelligence advantages, a lower complexity identification method is proposed in this work. We utilized supervised learning algorithms to distinguish the direct link, first-order, and higher-order MPs of millimeter-Wave Vehicle-to-Infrastructure (V2I) communication. In particular, four algorithms namely KNN, and SVM, MLP, and LSTM have been applied. The characteristics of the multipath component including received signal strength and elevation and azimuth angle of arrival are considered as features to train the proposed models. The results showed that the accuracy rates of the classification are ranged between 96.70% and 84.0%. The best accuracy rate was 96.70% obtained by LSTM, followed by 94.47 % obtained by MLP. Whereas, 93.67% and 84.0% accuracy rats were achieved by KNN and SVM respectively.

1. Introduction

In recent years, the world moving towards autonomous driving technology in order to improve the quality of intelligent transportation systems [1]. Such technology required robust and precise vehicular localization method. Recently, there are several technologies available for vehicular localization such as GPS, wireless communications (vehicular networks), camera, radar, and lidar [2][3]. According to [4], wireless communication technology is the most promising for vehicular localization, it has several advantages over the rest technologies. Wireless communications technology includes Bluetooth, ZigBee, WIFI, and 5G and beyond.

However, the literature reported that the wireless technology (also called vehicular networks) is more suitable for vehicle localization due to the provided long rang and beat the weather conditions fluctuation. The vehicular networks have several architectures such as Vehicle-to-Vehicle (V2V), Vehicle-to-Vehicle (V2V), Vehicle-to-Pedestrian (V2P), and Vehicle-to-Network (V2N). However, the localization techniques of the vehicular networks can be categorized into free range and range-based (geometry-based). The range-based techniques have advantages over the free-rang based techniques.

Recently, 5G and mm-wave technology have been used in vehicular communications. The systems of this technology exhibit many properties such as large number of elements in antenna array (multiple input multiple output antenna) and providing narrow beam [5]. This makes the range-based techniques have more opportunities for achieving accurate localization, where estimating the characteristics of MPCs is more accurate [6].

The key point of the rang-based techniques is the ability of identifying the direct-link (DL) and the first-order (FO) of the MPCs [7]. Coexistence of the higher-order (HO) MPCs will degrade the localization accuracy. Unfortunately, in dense multipath environments, presences of combination of DL, FO, and HO of the MPCs inevitably, and the distinguish between these types of MPCs is complex task. In dense multipath environment such as urban environments, this task may be invalid particularly when the conventional techniques are applied. It is difficult to identify the DL and the FO MPCs using the statistics of the characteristics such as received power and delay time [4]. In conclusion, identifying the type of the propagation path in dense multipath environments is challenging [8]. Therefore, identifying the type of the MP is vital and important prior step for the rang-based localization techniques.

However, the state of the art reported that there are several researchers have attempted to solve this issue with different methods by using the available information of the received signal paths. For example, the proximity relationship was used in [9] to differentiate the direct and FO MPCs from the HO. The time of arrival (TOA) of the propagated paths have been used for normalizing the weight factor. Therefore, the HO MPCs are identified as outliers. The authors in [10] utilized angle of departure (AOD) and angle of arrival (AOA) jointly with map information of indoor office environment to identify the FO MPCs. The authors in [8] proposed an iterative method based on generalized likelihood ratio test approach to distinguish the FO and HO MPCs.

Nowadays, supervised learning algorithms, including machine learning and deep learning, become popular in data mining aspects. It has an efficient performance for solving the non-linear problems for regression and classification. In the localization area, the supervised learning algorithms have been widely used for identifying LOS and NLOS (classification algorithms) [11][12] and for estimating the users' position (regression algorithms) [13][14][15]. However, to the best of the authors knowledge, still not adopted for identifying the type of the propagation path of mm-wave V2I communication in urban scenario. In general, offering the sufficient amount of sampling and labeling assumptions are considered the main impediment of applying the supervised learning algorithms for identifying the type of the MPCs in the real world. To overcome these issues, the researchers relied on the simulation techniques. However, ray tracing techniques are the most reliable for generating the information of signal propagation [16]. Its reliability has been validated in indoor [17][18] and outdoor [19][20] scenarios. Therefore, the ray tracing technique is adopted by this research to conduct the measurement of the characteristics of the MPCs.

Recently, several supervised algorithms have been presented for classification purposes. In this paper, we are going to evaluate and compare the effectiveness of traditional and modern supervised algorithms on the type of MPCs classification. To this end, four algorithms, namely K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Multilayer Perceptron (MLP), and Long Short-Term Memory (LSTM), have been selected based on the following considerations. The KNN is a simple yet effective algorithm for classification, making minimal assumptions about the data distribution. It can handle non-linear relationships between features. The SVM is a powerful classification algorithm that aims to find the optimal hyperplane to separate classes while maximizing the margin. It can handle both linear and non-linear problems through the use of different kernels (e.g., linear, radial basis function, polynomial). The MLP is capable of modeling complex, non-linear relationships in data. It can approximate any continuous function, making it a versatile choice for classification tasks. The LSTM is a specific type of recurrent neural network (RNN) that excel in sequential data analysis, making it more suitable sequence-based classification tasks. LSTM can capture dependencies over longer time steps, which is beneficial for certain types of numerical data.

In summary, this paper utilizes the supervised learning based on classification algorithms for identifying the type of MPCs. The available characteristics of the received MPC, including received power and angular information, are considered as features to train the proposed models. In particular, four algorithms namely KNN, SVM, MLP, and LSTM will be applied to identify the type of the MPCs. The contributions of this work are summarized as follows: (1) In order to generate a reliable dataset, we design a realistic V2I scenario in dense multipath environment (dense urban environment). A ray tracing simulator is used to mimic a real multipath propagation of V2I communication, (2) Based on the supervised classification algorithm, we proposed an efficient approach to distinguish the direct, first-order, and higher-order paths.

The rest of this paper is organized as follows. The configuration of the considered scenario is explained in Section 2. Section 3 presents the proposed supervised learning algorithms that will be applied for MPCs identification including machine learning and deep learning. In Section 4, we evaluate and discuss the performance of the proposed methods. Finally, the conclusions and recommendations are drawn in Section 5.

2. Simulation Setup and V2I Scenario Description

The aim of this work is identifying the MPCs type of downlink of mm-wave V2I communication scenario by utilizing the supervised learning algorithm. However, in order to generate a simi-realistic dataset to train the supervised models, we utilize the ray tracing technique. To this end, a commercialized ray tracing simulator, namely Wireless InSite developed by Remcom, is utilized to mimic a realistic V2I communication scenario in urban environment. First, a real 3D geometric structure of an urban environment (e.g., Kuala Lumpur City Centre (KLCC), Jalan Ampang is imported to the ray tracing simulator as shown in Fig. 1. The electromagnetic (EM) properties of materials of the buildings, terrain, and foliage are listed in Table 1. These properties are considered based on the International Telecommunication Union (ITU) recommendations. After that, a millimeter-Wave Vehicle-to-Infrastructure (V2I) communication scenario is constructed with specifications according to [21] and [22]. The transmitter (the red circle) is located at coordinates x=295.348m and y=312.424m with a height 10m, whereas a grid of receivers is uniformly distributed to cover the interested area to represent the vehicle locations, i.e., the vehicle is assumed to be stationary during each measurement snapshot. The separated distance between the receivers is set to 1m. For simplify the simulation, the antenna is assumed to be omnidirectional with a high gain instead of swapping the directional antenna. The specifications of the V2I configuration are listed in Table 2.

During the simulation running, the receivers measure the signal and extract the characteristics of the MPCs from the channel impulse response (CIR) which can be represented as

$$H(t) = \sum_{n=1}^{N} p_n e^{-j\emptyset k} \,.\, \delta(\gamma_n) \,.\, \delta(\emptyset_n) \,.\, \delta(\theta_n) \tag{1}$$

where, N is the number of received MPCs. p_n is complex amplitude. γ_n is delay spread of the n^{th} MPC. $\emptyset_n$ and θ_n are the departure and arrival angular information respectively. Finally, the recorded data are labeled based on visual observation into three classes. Each class is relative to each type of the MPC.

Table 1 *Electromagnetic properties of materials*

Features	Material	Type	Permittivity	Conductivity S/m
Buildings	Concrete	Layered Dielectric	5.31	0.015
Terrain	Wet earth	Dielectric Half-Space	20.00	0.02
Foliage	Leaf	Biophysical	26	0.39

Table 2 *V2I configurations*

Parameter	Specification
Antenna Type	Omnidirectional
Antenna Polarization	Vertical
Antenna Gain	27 dBi
Antenna Height	Tx = 10 m, Rx = 2 m
Transmitted Power	32.0 dBm
Frequency	28 GHz
Ray tracing Technique	SBR
Model	Full 3D

Fig. 1 *3D geometric structure of KLCC*

3. Supervised Learning for MP Identification

In this section, we discuss the considered supervised algorithms to distinguish the direct, first-order, and higher order MP. They considered supervised algorithms including traditional ML and deep learning algorithms.

In the context of ML, k-nearest neighbors (KNN) and linear support vector machines (SVM) are considered the most popular traditional supervised learning algorithms. They have been successfully applied for classification tasks. In this research we considered these algorithms as baseline for identifying the MP type. However, compared to KNN algorithm, SVM exhibits lower complexity and is easier to interpret. But, on the other hand, KNN provides capability to find a complex pattern. In SVM algorithm, a hyperplane is used to separate the classes (the type of the MPC). The hyperplane (H) is selected by minimizing equation (2).

$$H = \frac{1}{n+m} \sum l_i \quad (2)$$

where, n is the width of margin, m is a hyperparameters (typically selected by cross-validation), and l is penalty for point i. However, contrary to SVM, KNN algorithm is a non-parametric. It does not assume particular hyperplane to separate the classes. It works by voting system based on the mean of k (number of nearest neighbors) to determine the type of MP. Typically, KNN is regularized by selecting the k value using cross-validation.

In recent years, deep learning algorithms have been utilized to solve a complex problem. They have outperformed the ML. However, there are several deep learning algorithms that have been developed in several aspects. While no one network is considered perfect, some algorithms are better suited to perform specific tasks. MLP algorithm provided an efficient performance for classification of numerical data. Therefore, it has been adopted in this work. Basically, the MLP belongs to feedforward neural networks. Its structure consists of an input layer, multiple layers that have activation functions (hidden layers), and output layer. The recorded information of the signal MP is fed as sequence into the considered MLP.

LSTM belongs to RNN. It is useful in time-series prediction owing to it remembering the previous input. It has a strong ability to bring out strong patterns. Essentially, LSTM is created to overcome the feedforward issues such as considering only the current input. Therefore, the LSTM classification decision is taken based on the previous inputs in addition to the current input. However, in order to evaluate the proposed classifiers, they are tested by using the same test dataset. Furthermore, for the sake of comparison, the performance of the proposed classifiers is compared in terms of major metrics accuracy, precision, recall and F1-score.

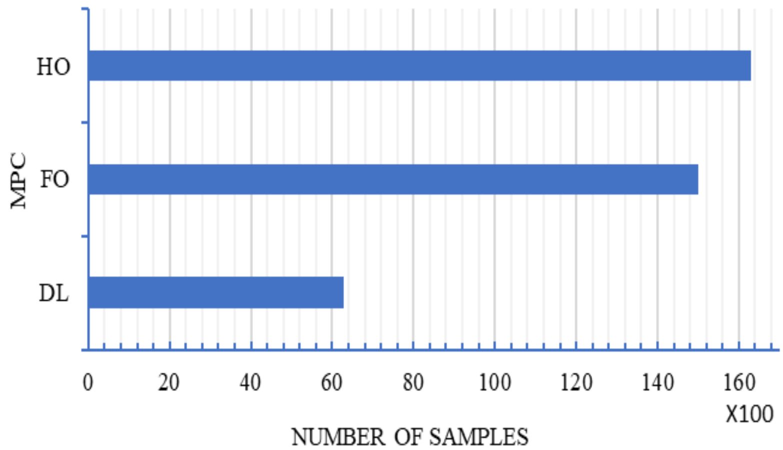
4. Classification Results and Discussion

This section shows the evaluation results of the proposed classifiers. We will present a brief analysis of the generated dataset. Then, we will compare the performance of the proposed algorithms. It is worth mentioning that the proposed classifiers are trained by using the same training dataset and then tested by using same dataset. However, the generated dataset consists of three types of constructed paths with a total of 37620 samples (i.e., received MPCs). These paths were recorded at 8137 locations (a grid of the distributed receivers) for both LOS and NLOS scenarios. Each sample (received path) contains three features vector including received power, azimuth angle of arrival (AAOA), and elevation angle of arrival (EAOA).

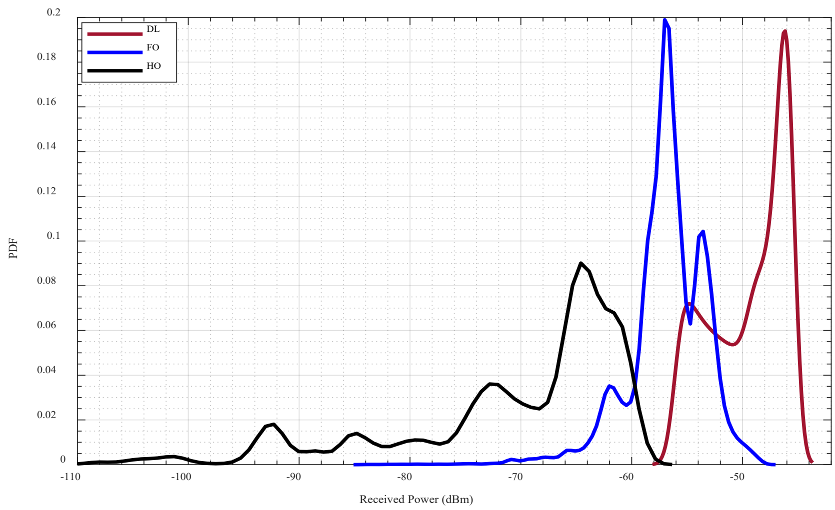
The statistics of the collected MPCs are shown in Fig. 2 (a). It is obvious that from the histogram of the number of samples, the number of HO samples and FO samples are higher than the DL samples. This is consistent with the propagation phenomenon in a complicated environment, where the signal arrived to the receiver with several reflected MPCs even when the Tx and Rx are in LOS. In conclusion, the dataset showed an imbalanced number of DL, FO, MO MPs. Therefore, a random over-sampling method is used in order to remove the dataset imbalances. However, to visualize the challenge of identifying the type of MPCs, the probability density function (PDF) of the MPCs features is presented in Fig. 2 (b, c, and d). It is clear that, all the three features showed overlapped area. For example, the recorded received power for DL, FO, and HO are ranged at intervals from -45.7395 to -56.0677 dBm, -48.2161 to -83.8980 dBm, and -59.4691 to -110.35 dBm respectively. In conclusion, identifying the MPC type is a crucial challenge. This proves that the iterative methods may provide a lower identification performance.

However, to prepare the dataset for training and testing the proposed classifiers, the balanced dataset is randomly divided into 80% for training and 20% for testing the classifiers.

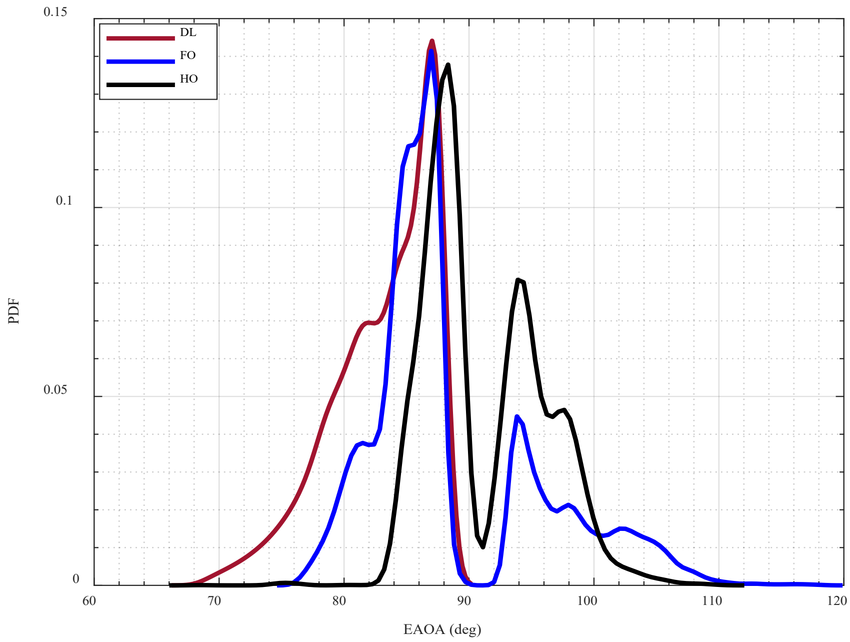
MATLAB application has been used to design and implement the proposed classifiers. Since each classifier has specific hyperparameters; therefore, the hyperparameters are optimized individually based on the empirical method. A tradeoff between the accuracy, precision, and recall was considered for selecting the optimal hyperparameters. The optimized hyperparameters are listed in Table 3.



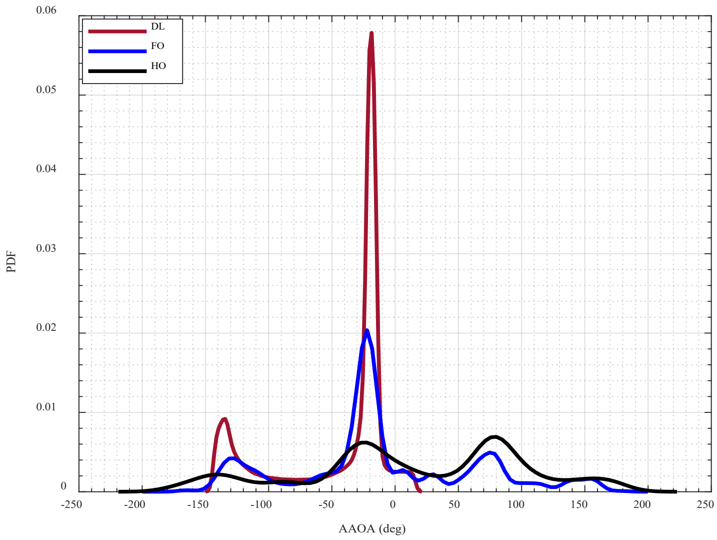
(a)



(b)



(c)



(d)

Fig. 2 *Dataset statistics*

MATLAB application has been used to design and implement the proposed classifiers. Since each classifier has specific hyperparameters; therefore, the hyperparameters are optimized individually. A tradeoff between the accuracy, precision, and recall was considered for selecting the optimal hyperparameters. The optimized hyperparameters are listed in Table (3).

Table 3 *Optimized hyperparameters*

Classifier	Optimal hyperparameters
SVM	Kernel function: Gaussian,
KNN	K=7, Distance: Euclidean,
MLP	Layer sizes: [20 20 20], Activations: relu, Output Layer Activation: softmax.
LSTM	3 LSTM layers, No. Hidden Units: 150, Activation Function: sigmoid, Output Layer Activation: softmax.

The performance of the trained classifiers was evaluated by calculating the overall classification accuracy, and further analyzed using major metrics (Precision, Recall, and F1_Score) as presented in Table 4. Furthermore, the confusion matrices were calculated, as shown in Fig. 3, to visualize the classification results in terms of classes misclassification. As presented in Table 4, all the metrics scores demonstrate a very good performance of classification. The best results for each metric were achieved by LSTM classifier. The accuracy rate, precision, recall, and F1_score was 96.70%, 96.81%, 96.72%, and 96.76% respectively. The MLP classifiers come in the second order, whereas the worst accuracy rate was achieved by SVM classifier, and it was 84%. However, this work is considered as the prior step for geometric based localization methods. In these methods (i.e., geometric based localization), the localization error may primarily occur in two cases. The first case is when HO-MP is wrongly predicted as either FO-MP or DL-MP. The second case is when FO-MP is wrongly predicted as DL-MP. Therefore, in this case, we must assess the performance of the proposed classifiers in terms of HO-MP and FO-MP misclassification. To do that, we represented the performance of the proposed classifiers in the form of confusion matrices, as shown in Fig. 3. The HO-MP misclassification for each classifier is highlighted by green circles whereas the FO-MP misclassification is highlighted by red circles. From the figure, it is clear that the LSTM achieved the lowest HO-MP and FO-MP misclassification. The HO-MP misclassification was 0.7%, whereas the FO-MP was 3.1%. The HO-MP and FO-MP misclassification for MLP were 6.9% and 2.4% respectively. In summary, we can confirm that the performance of LSTM classifier outperformed the rest of the classifiers.

Table 4 *Results of evaluating metrics*

Classifier	Accuracy	Precision	Recall	F1_Score
SVM	0.84	0.8403	0.8572	0.8487
KNN	0.9367	0.9366	0.9369	0.9368
MLP	0.945	0.9443	0.9448	0.9445
LSTM	**0.9670**	**0.9681**	**0.9672**	**0.9676**

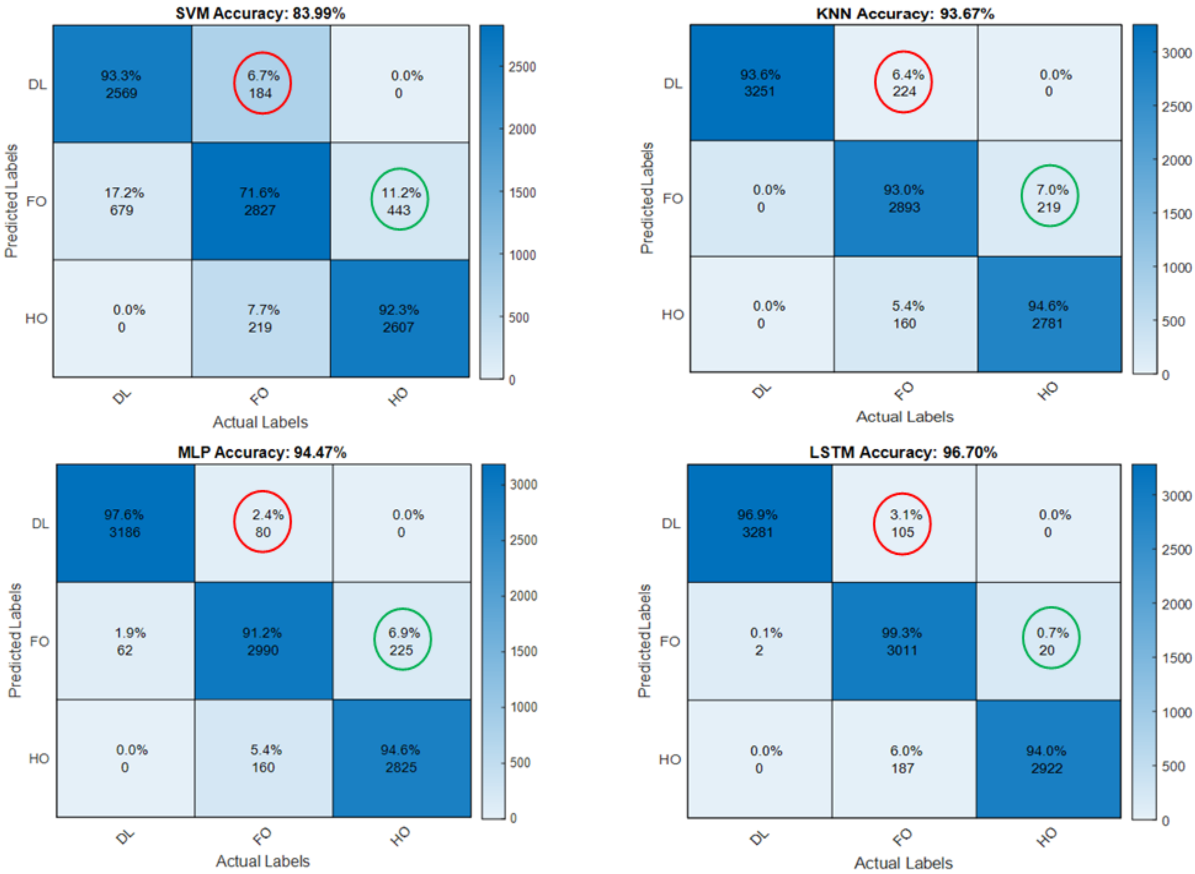


Fig. 3 *Confusion matrices*

5. Conclusion

Accurate identification on the type of the propagated MP is a prior step for geometric based localization methods. However, in this work, an efficient identification method based on supervised learning techniques is proposed to distinguish the DL-MP, FO-MP, and HO-MP. Four supervised classification algorithms namely, SVM, KNN, MLP, and LSTM have been proposed. The ray tracing technique has been utilized to generate the dataset. The results showed that the supervised methods provide a good classification accuracy with lower complexity compared to the iterative methods. The classification accuracy rate of the proposed algorithms ranged between 83.99% and 96.70%. The performance of deep learning algorithms (i.e., MLP and LSTM) outperformed the performance of the ML algorithms (i.e., SVM and KNN). In deep learning algorithms, the LSTM achieved better performance in terms of evaluation metrics and HO and FO misclassification comparing to the MLP.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Yaser A. Bakhuraisa, Azlan B. Abd Aziz;* ***data collection:*** *Yaser A. Bakhuraisa;* ***analysis and interpretation of results:*** *Yaser A. Bakhuraisa, Azlan B. Abd Aziz;* ***draft manuscript preparation:*** *All authors. All authors reviewed the results and approved the final version of the manuscript.*

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