Two Level Wi-Fi Fingerprinting based Indoor Localization using Machine Learning

Bharath Kumar*
IITRAM, Ahmedabad
bharathkumar.swargam.18e@iitram.ac.in

Manish Chaturvedi
IITRAM, Ahmedabad
manishchaturvedi@iitram.ac.in

Ram Narayan Yadav
IITRAM, Ahmedabad
ramnarayan@iitram.ac.in

ABSTRACT

Indoor localization is defined as the process of locating a user or device in an indoor environment. It plays a crucial role for first responders in disaster and emergency situations. In situations where the environment does not change much after an incident happens, fingerprint based indoor localization can be used for effective localization and positioning. Due to the growth in smartphone users in the last few years, indoor localization using Wi-Fi fingerprints has been studied by researchers. The measured Wi-Fi signal strength can be used as an indication of the distribution of users in various indoor locations. In disaster and emergency situations, localization services should be highly accurate and fast. We can model localization as a classification problem and address using machine learning (ML) approaches. However, these two requirements are conflicting since an accurate fingerprint-based indoor localization system needs to process a large amount of data, and this leads to slow response. This problem becomes even worse when both the number of floors and the number of reference points increase. To address this challenge, we use a two-level localization in order to improve both the accuracy and the response time. First, the fingerprint database is used to train ML models. The localization phase has two steps: (i) floor prediction, and (ii) reference point prediction on the predicted floor. For floor prediction, we use K-Nearest Neighbors (KNN) classification algorithm. Then we use various ML models such as Random Forest, Decision Tree, and Support Vector Machine. We use a dataset having two files with different floor numbers. Experiment results showed that random forest gives the best accuracy among other ML models. So two-level localization method is more suitable than single level localization in terms of localization accuracy and speed, and thus can be utilized in many applications.

CCS CONCEPTS

• **Computing methodologies → Machine learning algorithms**.

KEYWORDS

Disaster management, indoor localization, Wi-Fi fingerprint, K-Nearest Neighbour, Random Forest, ML models

*All authors contributed equally to this research.

ICDCN 2023, January 4–7, 2023, Kharagpur, India

ACM ISBN 978-1-4503-9796-4/23/01…$15.00
https://doi.org/10.1145/3571306.3571429

ACM Reference Format:
Bharath Kumar, Manish Chaturvedi, and Ram Narayan Yadav. 2023. Two Level Wi-Fi Fingerprinting based Indoor Localization using Machine Learning. In *24th International Conference on Distributed Computing and Networking (ICDCN 2023), January 4–7, 2023, Kharagpur, India.* ACM, New York, NY, USA, 6 pages. https://doi.org/10.1145/3571306.3571429

1 INTRODUCTION

Due to the development of artificial intelligence and machine learning technology, various applications in the domain of medicine, industry, disaster management, and surveillance have emerged rapidly. Many of the related services such as indoor navigation, intelligent robots, internet of things (IoT) applications, and smart architectures require the location of a user or a device in an indoor environment. These services are called location based services. For an instance, the disaster response personnel can locate the people quickly with indoor localization in case a fire incident occurs in a building, this helps them to get closer to those to be rescued and evacuate them [7, 14]. Most of these applications require high accuracy of localization very fast. So, there is a need of localization to improve both the accuracy and the response time. Though, the global positioning system (GPS) is widely used for localization in outdoor environments, the usability of GPS is not satisfactory in the indoor environments due to its complexities such as varying shapes, and sizes objects, presence of stationary and moving objects (e.g. furniture and people), different structures of indoor environments such as walls, floors. Different thicknesses and types of walls have different impacts on the accuracy of indoor localization. These factors significantly affect line-of-sight (LOS) and non-line of sight (NLOS) radio signal propagation causing unpredictable attenuation, scattering, shadowing, and blind spots. Therefore, the development of indoor localization becoming more and more important for realizing these applications. Indoor localization is the process of obtaining a device or user location in an indoor environment. With the demand for high precision and cost-effective localization for many applications, several approaches have been proposed by researchers.

Indoor localization techniques can be divided roughly in two categories. (i) Based on radio waves: These techniques include Received Signal Strength (RSS), and Channel State Information (CSI), Time of Flight (ToF), Time Difference of flight (TDoF), Angle of Arrival (AoA), Time of Arrival (ToA), Time Difference of Arrival (TDoA) [12, 13], (ii) Based on a video camera: the techniques in this category capture the images with a camera (color camera or infrared camera) and use image processing techniques to estimate the location of the object [10, 17]. In this paper, we focus on radio-wave localization. Most of the techniques based on radio waves include using Wi-Fi, acoustic, blue-tooth, and cellular signals [19].

Fingerprint localization with the help of Wi-Fi is one the most common method used these days [5].

Fingerprinting is a popular method in radio-wave indoor localization and requires a survey of the environment where the localization system needs to be placed. The fingerprinting technique consists of two phases: (i) offline phase: a site survey is done to collect radio signals such as RSSI, CSI etc. from different access points such as Wi-Fi at many reference points of known locations. Thus, each reference point is represented by its fingerprint. These fingerprints of the site are stored in a database, (ii) online phase: the real-time measurements match the stored offline fingerprints to estimate the user location [18].

Fingerprinting based methods provide higher accuracy if more reference points data is collected during the offline phase to construct the fingerprint dataset. However, constructing the fingerprint database for larger reference points is costly in terms of manpower, cost and time. Also for dynamic environments, the offline fingerprint database must be recreated. So, we assume the environment where fingerprinting based indoor localization is employed is mostly static in nature. Also, the proposed model was built using data from a wifi signal. Other signals can be associated with the model, but we focused on the minimal requirement of physical infrastructure, which is the most general case. Wifi is the most widely accepted and used signal in most parts of the world. So, we focused on using the data of a wifi signal, excluding all other data which require some physical infrastructure.

The rest of this paper is organized as follows: Section II presents the related work. In Section III we present the methods and experimental datasets used in this paper. Section IV shows the experimental results. The paper is concluded in Section V.

2 RELATED WORK

A number of research papers have been done on indoor localization. A detailed survey on approaches used for indoor localization is done by F. Zafari et al. [20]. Most of the radio-wave technologies have been studied and implemented using Bluetooth, Zigbee, WiFi, and UWB (Ultra Wideband). Since most of the current smart devices such as phones, and laptops are WiFi enabled and most of the environments are equipped with WiFi access points, WiFi fingerprinting techniques can be employed without the need for additional infrastructure and costs. Reported papers discussed various ML algorithms including Neural Networks (NN), Support Vector Machine (SVM), and k-Nearest Neighbors (K-NN), etc. Authors highlighted that most of the ML based techniques use RSSI fingerprints to obtain device or user location. In fingerprinting approach, machine-learning methods are broadly used in the literature for creating databases and predicting the location. Various machine learning techniques such as K-Nearest Neighbor (KNN), Artificial Neural Networks (ANNs), Support Vector Regression (SVR), and Deep Neural Networks have been proposed for indoor localization in literature [1, 6, 9, 11]. Authors in [2] explored various machine learning techniques, such as support vector machines, spline models, decision trees, and ensemble learning, for received signal strength indicator (RSSI)-based ranging in LoRa networks. Based on the experiment and the results their study shows that the ML approach toward RSSI fingerprinting provides promising results. Nowadays, deep learning algorithms are popular and outperform many traditional machine learning algorithms in terms of accuracy, many researchers have focused their attention on deep learning-based fingerprinting and tracking algorithms. Junhang Bai et al. proposed a Wi-Fi fingerprint-based indoor localization by integrating a sparse autoencoder and a recurrent neural network (RNN) [3]. Most of the above reported work is either computationally intensive or required more time for localization. So, we aim to propose a fast and more accurate ML model for indoor localization.

2.1 Our contributions

As we have discussed that in disaster and emergency situations, localization services should be highly accurate and fast. Since these two requirements are conflicting because an accurate fingerprint-based indoor localization system needs to process a large amount of data, and this leads to slow response. To address this challenge, we propose a two-level localization. The localization phase has two levels: (i) floor prediction, and (ii) reference point prediction on the predicted floor. For floor prediction, we use K-Nearest Neighbors (KNN) classification algorithm. For the second level, we use Random Forest. We show that two-level localization method is more suitable than single level localization in terms of localization accuracy and speed, and thus can be utilized in many applications.

3 METHODOLOGY

We use a two-level localization in order to improve both the accuracy and the response time. First, the fingerprint database is preprocessed and used to train ML models. The localization phase has two steps: (i) floor prediction, and (ii) reference point prediction on the predicted floor. For floor prediction, we use K-Nearest Neighbors (KNN) classification algorithm. Then we use various ML models such as Random Forest, Decision Tree, and Support Vector Machine. Experiment results showed that random forest gives the best accuracy among other ML models so we use Random Forest for reference point prediction on the predicted floor. We looked over many datasets on the internet and selected the appropriate ones. We use two datasets for our experiment named Dataset 1 and Dataset 2. The dataset 1 is an "energy-efficient indoor localization wifi-fingerprint dataset" available online [16]. The second dataset is "wlan rss indoor measurement data" published by the Tampere University of Technology for our experiment [8]. Dataset 2 has two files with different floor numbers.

3.1 Study on Dataset 1

Initially, we used energy-efficient indoor localization wifi-fingerprint dataset available online [16] in our study. This dataset consists of two files i.e., training and test cases in .json format. Each file consists of various features including list of Access Points (APs), and location coordinates (latitude, longitude, and floor information) where the sample was captured. The training case consists of 7175 data records collected from 489 different locations, whereas the testing case consists of 390 data records. We processed this dataset (such as reading data from .json file using the pandas library) so that we can apply machine learning algorithms to it. Machine learning algorithms like linear regression, K-Nearest Neighbors regressor, and Decision Tree regressor were applied to the dataset [16]. The results of these models show that the data was overfitting the model. The models are learning the location attributes associated to the APs since there are fewer changes in attributes for every sample (i.e., there are nearly no changes in features when the data sample is being changed). After doing this analysis, we came to the conclusion that this dataset is not useful for our study. So, we started exploring other WiFi fingerprinting datasets. The analysis of the other dataset is followed in the next section.

We use performance metrics such as R^2 score, distance error, and floor accuracy for evaluations of different ML algorithms on dataset [8].

3.2 Study on Dataset 2

The dataset 2 is published by Tampere University [8], which helps to test the Wifi fingerprint-based localization techniques. The dataset consists of two .csv files. These are the data collected from 2 buildings in Tampere University. The first file consists of 1478 samples taken in the first building which has 4 floors. Each data point consists of 312 attributes, of which 309 are RSSI values obtained by various wifi access points(WAP), and 3 are location coordinates (latitude, longitude, floor). The Received Signal Strength Indicator (RSSI) indicates the power level being received by the device. The higher the RSSI value, the better and stronger the signal received. During the preprocessing step, in case the signal from an access point is not detected we set the RSSI value as 100.

The coordinates are taken with respect to a predefined origin and measured in meters. The RSSI values of detected WAPs range from -100 to 0 (integers), and 100 if WAP is not detected.

The second file consists of 583 samples taken in the second building which has 3 floors. It consists of 357 attributes (354 WAPs and 3 location coordinates). They follow the same descriptions as above. The data from these two buildings are separate, without any implicit relation. The laptop used for the experiment was Intel i5 8th gen with 8 Gb RAM.

Various machine learning models are built to analyze the patterns in the data in the best way. We have made two separate models, one for predicting latitude, and longitude (reference point), and the other for floor prediction. We used regression techniques such as Random Forest, Decision Tree, Support Vector Machines, and K-Nearest Neighbors for predicting the coordinates. Since the floors are a finite set of values, we applied classification using K-Nearest Neighbors. The classification models are analysed using accuracy. The regression models were analysed using R^2 score (the coefficient of determination). This R_2 score is calculated below in equation 1.

$$R^2(y,\hat{y}) = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{1}$$

where,

$$\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i \tag{2}$$

$$\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 = \sum_{i=1}^{n}\epsilon_i^2 \tag{3}$$

where y is the target variable (in our case it is the reference point i.e. latitude and longitude), $\hat{y}$ predicted target variable, and $\bar{y}$ is the mean of the target variable.

4 RESULTS

We used various APIs from scikit learn library [4, 15] to perform preprocessing and build the machine learning models. We divided the dataset into different splits of training and test sets, and observed the performance of various ML models as shown in Table 1. Out of them, 80% training data and 20% testing data split is giving the best results in all the models. Plots of each model as a distance error function are obtained as shown below. This function calculates the distance (in meters) between the actual location and the predicted location of the record (in test data). For the Random Forest model, around 87% of the data is having distance errors less than 10 meters for 1st file and around 83.7% for 2nd file, as shown in the Figures 2a and 2b, indicating a good prediction of location coordinates. Around 59% of the test data is having distance errors of less than 10 meters in the case of SVM model as shown in Figure 4a for file 1. The random forest is the best performing model for the location coordinates with an R^2 score of around 92% for the 1st data file, and 96% for the 2nd data file as shown in table 1. This Random Forest algorithm takes less training time in handling high dimensional data contrary to others, predicts efficiently even for large datasets (which is the case here), and prevents the overfitting issue by creating multiple decision trees. Figures 2c and 3a represent the histogram plots showing the distance error for k-Nearest Neighbors model for 1st file and 2nd file. Histogram plot for distance error of the Decision Tree model is shown in Figures 3b and 3c for the 1st file and 2nd file respectively. For SVM, Figures 4a and 4b show the distance between the predicted and actual location for 1st file and 2nd file respectively.

4.1 Floor prediction

k-Nearest Neighbor classification algorithm is used to classify the floor attribute. The Floor column is taken as the target variable and the rest of the columns are taken as input variables. This floor classification model gives an accuracy of around 93% for 1st data file and around 99% for the 2nd data file. The reason of higher accuracy for the 2nd one is due to less number of records. The confusion matrices of both models are also highlighted below as shown the Figure 4c and Figure 5a.

4.2 Two Levels Indoor Localization Model

In order to reduce the response time and improve the accuracy of the prediction, we developed a two-level localization model. We combine two models KNN and Random Forest for localization. As we have seen how each of the applied machine learning algorithms is performing, a two-level localization model is developed, which performs floor prediction first and then reference point prediction as shown in Figure 1. Also, finding a proper dataset for the study was one of the challenging tasks since most of them have distinct characteristics for location attributes. As seen in the (study of dataset 1), overfitting was also an issue with the datasets.

We use KNN classifier called model 1 for floor prediction and Random Forest Regressor called model 2 for the reference point prediction on the predicted floor. The reason for choosing the Random Forest Regressor for model 2 is because of its best performance compared to other algorithms as seen in Table 1. There is a requirement to develop a combined model, both the models (model1 and

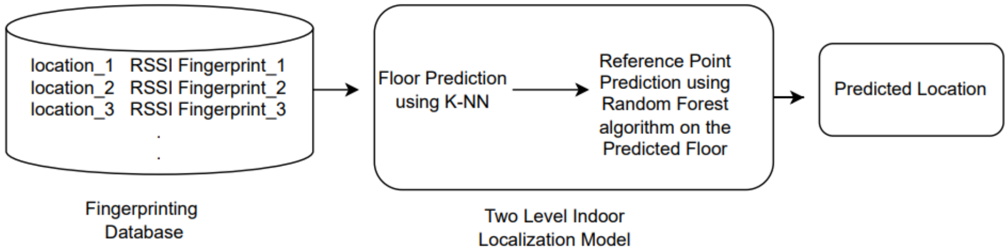


Figure 1: Two Level Indoor Localization Model

model 2) should have the same training and testing data records. Model 1 has the same characteristics which were designed earlier for floor prediction (4.1). However, for model 2, few steps were carried out on data applying to it. Data from the floor column of the original dataset was attached to the training data for model 2 by matching the indexes of training data in model 1. So that we are ensuring both the models have the same training data (except the floor attribute added in training data records for model 2). For the testing case, the predicted floor values from model 1 were appended to the testing data of model 2 by matching the indexes of testing data in model 1. Using this testing data in model 2, the location coordinates were predicted. We carried out the above discussed preprocessing on both data files. After training the models, the R^2 scores are 95.6% and 93.7% for the 1st and 2nd models respectively for the 1st data file. For the 2nd data file, 94.8% and 94.3% for the model 1 and model 2 respectively. The confusion matrix for data file 1 and data file 2 are shown in the Figures 5b and 5c. For the two-level indoor localization model, around 87.1% of the data is having distance error of fewer than 10 meters for 1^{st} file, as shown in the Figure 6. For 2^{nd} file, approx. 83% of the data is having distance errors less than 10 meters, as seen in figure 7. Both these conclude that the model is able to predict the location coordinates with good accuracy which is evident from the above model.

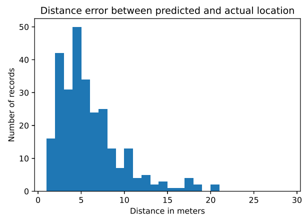
To analyze the difference in response time of the models, we measure the time required during the testing phase (20% of the whole dataset on file 1). To show the advantage of our two-level localization, we measure the time required in the testing phase of the Regression Tree (RT) and then compared it with our two-level localization model. We noticed the improvement in terms of the percentage of response time. We noted that the two-level localization model takes 8-10 % less time in the testing phase as compared to the RT model. This shows the benefit of combining the models.

Regressor	Dataset	Test Size	r2_score	CV_score in% 10-folds	Mean Absolute Error
K Nearest Neighbors	Tampere1	0.5	0.896	89.09	0.143
		0.4	0.907	89.57	0.127
		0.3	0.918	90.15	0.117
		0.2	0.918	91.07	0.1108
	Tampere2	0.5	0.909	87.76	0.119
		0.4	0.9176	89.73	0.103
		0.3	0.905	91.67	0.123
		0.2	0.9503	93.05	0.073
RandomForest	Tampere1	0.5	0.901	89.24	0.195
		0.4	0.911	90.07	0.1801
		0.3	0.9163	91.19	0.177
		0.2	0.9264	92.05	0.149
	Tampere2	0.5	0.914	90.43	0.183
		0.4	0.924	92.69	0.157
		0.3	0.927	94.32	0.143
		0.2	0.961	94.73	0.111
Decision Trees	Tampere1	0.5	0.788	77.22	0.161
		0.4	0.778	76.23	0.1604
		0.3	0.819	77.82	0.144
		0.2	0.823	80.23	0.11
	Tampere2	0.5	0.8731	85.93	0.11
		0.4	0.8804	89.41	0.09
		0.3	0.874	90.83	0.09
		0.2	0.939	92.22	0.05
Support Vector Machines	Tampere1	0.5	0.802	80.08	0.189
		0.4	0.8172	81.59	0.183
		0.3	0.839	83.11	0.178
		0.2	0.852	84.16	0.171
	Tampere2	0.5	0.64	59.95	0.12
		0.4	0.68	64.95	0.114
		0.3	0.71	70.20	0.117
		0.2	0.761	73.43	0.086

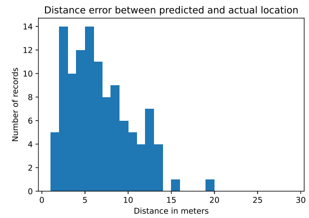
Table 1: Scores of models on dataset using different Regressors

5 CONCLUSIONS

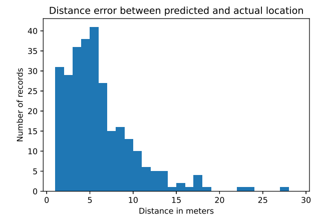
To address the indoor localization problem, we use a two-level localization in order to improve both the accuracy and the response time. The localization phase has two steps: (i) floor prediction, and (ii) reference point prediction on the predicted floor. For floor prediction, we use K-Nearest Neighbors (KNN) classification algorithm. Then we use various ML models such as Random Forest, Decision Tree, and Support Vector Machine. We use a dataset having two files with different floor numbers. The proposed approach is tested using two indoor data sets. Experiment results showed that Random Forest gives the best accuracy among other ML models. So we used Random Forest in the second step of localization. We show that the two-level localization method is more suitable than single level localization in terms of localization accuracy and speed, and thus can be utilized in many applications. The goal of addressing this problem as a classification problem needs to be explored further using various deep learning algorithms utilizing other related attributes such as channel state information (CSI) in real settings. One of the limitations of this work is WiFi fingerprinting based methods are not suitable for dynamic environments. To address this limitation, WiFi and other attributes such as wave fingerprints may be integrated for indoor localization in a dynamic environment.



(a) Histogram plot showing the distance between the predicted and actual location of the Random Forest model for 1st file

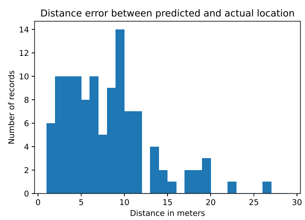


(b) Histogram plot showing the distance between the predicted and actual location of the Random Forest model for 2nd file

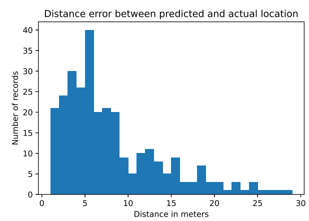


(c) Histogram plot showing the distance between the predicted and actual location of the K-Nearest neighbors model for 1st file

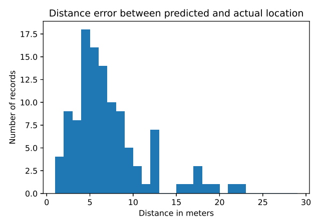
Figure 2: Histogram showing the accuracy of models



(a) Histogram plot showing the distance between predicted and actual location of the K-Nearest neighbors model for 2nd file

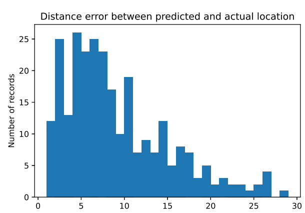


(b) Histogram plot showing the distance between the predicted and actual location of the decision tree model for 1st file

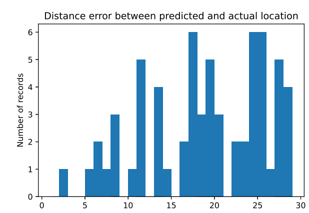


(c) Histogram plot showing the distance between the predicted and actual location of the decision tree model for 2nd file

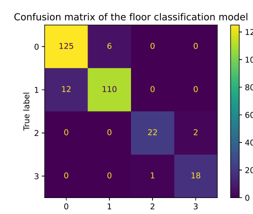
Figure 3: Histogram showing the accuracy of models



(a) Histogram plot showing the distance between the predicted and actual location of the Support Vector Machine model for 1st file

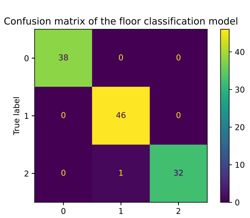


(b) Histogram plot showing the distance between the predicted and actual location of the Support Vector Machine model for 2nd file

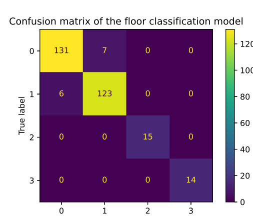


(c) Confusion Matrix of the classification model for floor prediction of 1st data file using KNN classifier

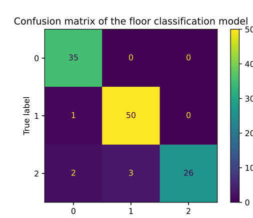
Figure 4: Histogram and confusion matrix showing the accuracy of models



(a) Confusion Matrix of the classification model for floor prediction of 2nd data file using KNN classifier



(b) Confusion Matrix of the final model for floor prediction of 1st data file using KNN classifier



(c) Confusion Matrix of the final model for floor prediction of 2nd data file using KNN classifier

Figure 5: Confusion matrices of different models

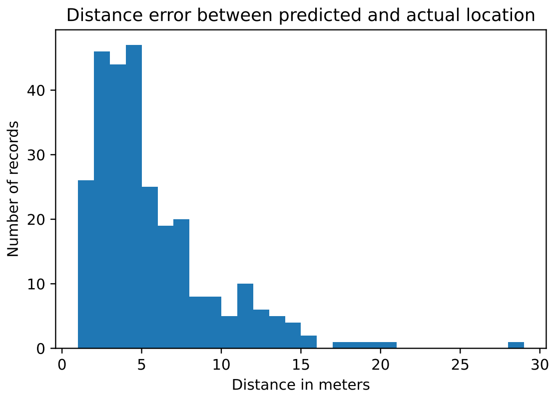


Figure 6: Histogram plot showing the distance between the predicted and actual location of the final model for 1st file

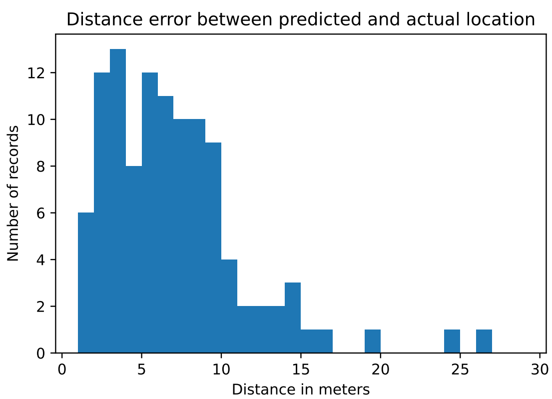


Figure 7: Histogram plot showing the distance between the predicted and actual location of the final model for 2nd file

ACKNOWLEDGMENTS

This work was supported by the SERB-DST, Government of India under Grant SRG/2020/000575.

REFERENCES

[1] Abebe Belay Adege, Yirga Yayeh, Getaneh Berie, Hsin-piao Lin, Lei Yen, and Yun Ruei Li. 2018. Indoor localization using K-nearest neighbor and artificial neural network back propagation algorithms. In *2018 27th Wireless and Optical Communication Conference (WOCC)*. IEEE, 1–2.

[2] Mahnoor Anjum, Muhammad Abdullah Khan, Syed Ali Hassan, Aamir Mahmood, Hassaan Khaliq Qureshi, and Mikael Gidlund. 2020. RSSI fingerprinting-based localization using machine learning in LoRa networks. *IEEE Internet of Things Magazine* 3, 4 (2020), 53–59.

[3] Junhang Bai, Yongliang Sun, Weixiao Meng, and Cheng Li. 2021. Wi-Fi fingerprint-based indoor mobile user localization using deep learning. *Wireless Communications and Mobile Computing* 2021 (2021).

[4] Lars Buitinck, Gilles Louppe, Mathieu Blondel, Fabian Pedregosa, Andreas Mueller, Olivier Grisel, Vlad Niculae, Peter Prettenhofer, Alexandre Gramfort, Jaques Grobler, Robert Layton, Jake VanderPlas, Arnaud Joly, Brian Holt, and Gaël Varoquaux. 2013. API design for machine learning software: experiences from the scikit-learn project. In *ECML PKDD Workshop: Languages for Data Mining and Machine Learning*. 108–122.

[5] Xi Chen, Hang Li, Chenyi Zhou, Xue Liu, Di Wu, and Gregory Dudek. 2022. Fidora: Robust WiFi-based Indoor Localization via Unsupervised Domain Adaptation. *IEEE Internet of Things Journal* (2022).

[6] Amira Chriki, Haifa Touati, and Hichem Snoussi. 2017. SVM-based indoor localization in wireless sensor networks. In *2017 13th international wireless communications and mobile computing conference (IWCMC)*. IEEE, 1144–1149.

[7] Alessandro Depari, Alessandra Flammini, Daniela Fogli, and Paola Magrino. 2018. Indoor localization for evacuation management in emergency scenarios. In *2018 Workshop on Metrology for Industry 4.0 and IoT*. IEEE, 146–150.

[8] J. Talvitie E.S. Lohan. 2015. "WLAN RSS indoor measurement data", Tampere University of Technology.

[9] Xu Feng, Khuong An Nguyen, and Zhiyuan Luo. 2022. A survey of deep learning approaches for WiFi-based indoor positioning. *Journal of Information and Telecommunication* 6, 2 (2022), 163–216.

[10] Weipeng Guan, Xin Chen, Mouxiao Huang, Zixuan Liu, Yuxiang Wu, and Yingcong Chen. 2018. High-speed robust dynamic positioning and tracking method based on visual visible light communication using optical flow detection and Bayesian forecast. *IEEE Photonics Journal* 10, 3 (2018), 1–22.

[11] Amir Haider, Yiqiao Wei, Shuzhi Liu, and Seung-Hoon Hwang. 2019. Pre-and post-processing algorithms with deep learning classifier for Wi-Fi fingerprint-based indoor positioning. *Electronics* 8, 2 (2019), 195.

[12] Chaur-Heh Hsieh, Jen-Yang Chen, and Bo-Hong Nien. 2019. Deep learning-based indoor localization using received signal strength and channel state information. *IEEE access* 7 (2019), 33256–33267.

[13] Wei Kui, Shiling Mao, Xiaolun Hei, and Fan Li. 2018. Towards accurate indoor localization using channel state information. In *2018 IEEE International Conference on Consumer Electronics-Taiwan (ICCE-TW)*. IEEE, 1–2.

[14] Hyo Won Lee, Wha Sook Jeon, and Dong Geun Jeong. 2017. A practical indoor localization scheme for disaster relief. In *2017 IEEE 85th Vehicular Technology Conference (VTC Spring)*. IEEE, 1–7.

[15] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. 2011. Scikit-learn: Machine Learning in Python. *Journal of Machine Learning Research* 12 (2011), 2825–2830.

[16] Jose Luis Salazar González, Luis Miguel Soria Morillo, Juan Antonio Álvarez García, Fernando Enríquez, and Antonio Ramon Jimenez Ruiz. 2019. Energy-efficient indoor localization WiFi-fingerprint dataset. https://doi.org/10.21227/49yg-5d21

[17] Hiroaki Santo, Takuya Maekawa, and Yasuyuki Matsushita. 2017. Device-free and privacy preserving indoor positioning using infrared retro-reflection imaging. In *2017 IEEE international conference on pervasive computing and communications (PerCom)*. IEEE, 141–152.

[18] Navneet Singh, Sangho Choe, and Rajiv Punmiya. 2021. Machine learning based indoor localization using Wi-Fi RSSI fingerprints: an overview. *IEEE Access* (2021).

[19] Min Yu, Shuyin Yao, Xuan Wu, and Liang Chen. 2022. Research on a Wi-Fi RSSI Calibration Algorithm Based on WOA-BPNN for Indoor Positioning. *Applied Sciences* 12, 14 (2022), 7151.

[20] Faheem Zafari, Athanasios Gkelias, and Kin K Leung. 2019. A survey of indoor localization systems and technologies. *IEEE Communications Surveys & Tutorials* 21, 3 (2019), 2568–2599.