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Wi-Fi Parmak İzi Kullanan İç Mekan Konum Belirleme Yöntemlerinin Karşılaştırılması

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ÖZET

Navigasyon sistemleri günlük hayatımızın vazgeçilmez bir parçası haline gelmiştir. Bunun gerçekleştirile bilinmesi için ise yerel konumun tespiti gereklidir. En yaygın kullanılan konum tespit metodu Global Konumlama Sistemidir (GPS). GPS sinyalleri kapalı alanlara çoğu zaman giremez. Bu sebeple kapalı alanlarda navigasyon için GPS kullanımı verimli değildir. Bu sebeple kapalı alanlarda navigasyon için konum belirleme işlemi için farklı metotlar geliştirilmiştir. Bunların başta gelen metodu Wi-Fi parmak izi ile pozisyon tahminidir. Bu konuda yapılmış birçok çalışma mevcuttur. Bu makalede, kablosuz ağ sinyal gücüne dayalı iç mekân konum tahmininde farklı makine öğrenimi yöntemlerinin performansı incelenmiştir. Bir veri kümesi kullanılarak yapay sinir ağları, k-NN, doğrusal regresyon, destek vektör makineleri, karar ağacı ve rastgele orman gibi yöntemlerin uygulanması ve sonuçların karşılaştırılması yapılmıştır. Kullanılan veri tabanı detaylı olarak açıklanmıştır. Bu veri tabanının makine öğrenme algoritmalarına nasıl uygulandığı izah edilmektedir. Sonuçlarda en başarılı metot ve başarıya etki eden faktörler değerlendirilmiştir.

Comparison of Indoor Location Determination Methods That Use Wi-Fi Fingerprinting

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ABSTRACT

Navigation systems have become an indispensable part of our daily lives. In order for this to be achieved, it is necessary to determine the local location. The most commonly used location determination method is the Global Positioning System (GPS). GPS signals often cannot penetrate closed areas. For this reason, using GPS for navigation in closed areas is not efficient. For this reason, different methods have been developed for position determination for navigation in closed areas. The primary method of these is position estimation via Wi-Fi fingerprint. There are many studies done on this subject. In this article, the performance of different machine learning methods in indoor location estimation based on wireless network signal strength is examined. Using a dataset, methods such as artificial neural networks, k-NN, linear regression, support vector machines, decision trees, and random forests were applied, and the results were compared. The database used is explained in detail. It is explained how this database is applied to machine learning algorithms. In the results, the most successful method and the factors affecting success were evaluated.

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INTRODUCTION

Rapidly developing technology makes our work easier at every point, both in our daily lives[1], [2], [3], [4] and in the industrial field [5], [6], [7], [8]. As a result of this developing technology, navigation systems have become an important part of our lives today. Thanks to navigation systems and mobile communication, people can see the shortest, fastest, and optimum route and provide transportation in cities they do not know. However, in order to perform this navigation, the current location must be determined. GPS is used for this purpose in open areas. Global Positioning System (GPS), known as Navstar GPS in its early days,[9] is a satellite-based radio navigation system. This system was developed and owned by the United States. The GPS is operated by the United States Space Force[10]. Although there are alternative navigation systems such as GLONASS, BeiDou, Galileo, Quasi-Zenith and India's recently announced NavIC, the most widely used and free one is GPS[11], [12], [13]. Satellite Navigation is based on a global network of satellites that transmit radio signals from medium earth orbit. The basic GPS service provides users with their local position information anywhere on or near the earth's surface, often to an accuracy of about 7.0 meters. To provide this service, GPS receivers must receive signals from at least four GPS satellites. These satellites have atomic clocks that provide extremely accurate time. Signals received from satellites contain the time and satellite information. Thus, position calculation is performed by comparing signals from at least four satellites[12]. It is possible to receive these signals via antenna for devices operating in areas that see the sky.

However, when GPS signals enter the indoor environment, they are weakened in the structure of the building. In most cases, it is not possible to use these signals for local location calculation in indoor environments. For this reason, different methods are tried in the literature for indoor positioning in indoor environments. Several widely used indoor location tracking methods encompass technologies such as ultrasound-based positioning, RFID systems for indoor navigation, ultra-wideband (UWB) techniques, Bluetooth-enabled location services, infrared positioning systems, ZigBee-based location identification, and WiFi-enabled indoor navigation solutions.

Indoor position estimation using the Wi-Fi fingerprinting method is frequently used to increase the accuracy of location determination systems in indoor areas (for example, shopping malls, hospitals, airports, and office buildings). GNSS (Global Navigation Satellite System) is a very effective positioning method in open areas. However, in indoor areas, satellite signals become weak or disappear completely. In this case, alternative methods are required for indoor positioning. This is where Wi-Fi fingerprinting comes into play. Wi-Fi networks are widely used in many indoor places. These networks emit signals through various access points (APs). Since these signals can be used to determine location without requiring additional equipment, they are a very economical navigation method. Positioning in indoor spaces is critical in a variety of application areas. Used in navigation and routing applications, it helps users find the shops, product stands, or doors they are looking for in large shopping malls or airports. While it can be used with an application on mobile phones, it is also possible to estimate coordinates for autonomous robots with hardware consisting of a very small and low-cost Wi-Fi receiver and a microcontroller. Apart from this, it also has benefits in areas such as security, tracking, customer analysis in stores, and emergency management.

In this study, different machine learning methods were used in indoor location estimation. Machine learning methods are used today in many areas from health, biomedical food, etc [14], [15], [16]. Although machine-learning methods are used in many areas, fine-tuning the parameters of the relevant machine-learning method on a problem-based basis seriously affects its performance [17]. For this reason, it is necessary not only to implement a method but also to set its parameters.

One of the first studies about Wi-Fi fingerprint indoor localization belongs to King et.al. In this study, Kint et.al. present a positioning system that combines 802.11 compliant network infrastructure and digital compasses to achieve accurate indoor positioning. The system samples signal strength values of access points and utilizes the user's orientation to determine the position. By using digital compasses to detect user orientation, the system overcomes the blocking effects caused by human bodies, achieving an average error distance of less than 1.65 meters in an experimental environment of 312 square meters. The paper also discusses the impact of various parameters on the system's performance and compares it with the RADAR system, demonstrating superior accuracy [18].

Torres-Sospedra et.al. introduce the UJIIndoorLoc database, a new database for indoor localization based on WLAN fingerprinting. The database covers three buildings with 4 or more floors and almost 110,000m2. The study states that the database was created by more than 20 users using 25 different devices and that this database can be used to test and compare localization algorithms, analyze device accuracy, improve WiFi coverage, and optimize WLAN access points. Additionally, a basic positioning system using the k-Nearest Neighbor rule has been developed to provide a baseline for comparison purposes. It is stated that positioning was made with an error of 7.9m with the Euclidean distance [19].

Unlersen, in 2022 discusses the use of RSSI signals for indoor location estimation. Artificial neural networks (ANN) have been used to estimate indoor locations using the power levels of Wi-Fi signals. RSSI data was preprocessed in three different ways: raw, path loss adapted, and exponentially transformed. Experiments show that the path loss adapted data set has the lowest error rate. Additionally, a systematic approach is presented to determine the number of neurons in the hidden layer of the ANN. In ANN training, the artificial bee colony (ABC) algorithm, which is an optimization algorithm with a fast convergence feature, was used. It is stated that the ABC-ANN method performs better than other popular machine learning methods in this database. The study showed that appropriate preprocessing has a significant impact on the prediction performance of artificial intelligence [20].

Yang et.al. proposes a method to compensate for non-line of sight (NLOS) errors in indoor positioning systems. The method introduces the concept of "virtual inertial point" and "environmental factor" and uses acceleration data from an inertial measurement unit (IMU) to compensate for NLOS errors in ultra-wideband (UWB) based indoor positioning systems. The proposed method is shown to improve positioning accuracy by approximately 80% in NLOS areas. Experimental results demonstrate the effectiveness of the method, outperforming existing UWB/IMU coupling compensation methods. The proposed method has low complexity and high computational efficiency [21].

The article that belongs to Lou et al presents a WiFi-based indoor localization framework that addresses the challenges of fluctuating received signal strength (RSS) in indoor environments. The proposed method involves fingerprint clustering using Gaussian mixture models in the offline phase to divide the localization area into subareas. Additionally, some machine learning methods like Random Forest, SVM, KNN are employed for location estimation. It is reported that the proposed method significantly reduces localization errors and increase accuracy without requiring hardware calibration. The study compares the performance of the proposed algorithm with other machine learning-based methods, showing superior results in terms of root mean square error (RMSE) [22].

Qin et al discuss a novel indoor positioning system called CCPos, which leverages Wi-Fi fingerprint technology for accurate indoor localization. The system combines a Convolutional Denoising Autoencoder (CDAE) with Convolutional Neural Networks (CNN) to enhance the accuracy and robustness of indoor Wi-Fi fingerprint localization. In order to compare the performance of proposed method, classical machine learning methods like random forest, k-NN and Gradient were also examined in the study. The UJIIndoorLoc dataset is used for testing method. It is reported that the mean positioning error is about 12.4m [23].

Anjum et al discusses the use of RSSI fingerprinting-based localization in LoRa networks using regression and machine learning (ML) models. It explores the application of ML approaches for localization and the design of safety and security systems in IoT ecosystems. The article highlights the importance of research, experimentation, and testing for practical implementations of these systems. The potential benefits of using ML in IoT systems, particularly in localization, are emphasized. In the article, the Smooting spline method has the best performance with the RMSE of 9.38m [24].

Polak et al present the use of machine learning in indoor location estimation based on received signal strength fingerprinting. Various ML-based classifiers are benchmarked to improve location fingerprinting results, including k Nearest Neighbors, Support Vector Machines, Random Forest, and Artificial Neural Networks. The Random Forest technique demonstrates high classification accuracy exceeding 99% in the scenarios tested [25].

Yildiz et al mentioned the importance of data mining in biomedical data applications. With this data, important results are obtained regarding the early detection, prevalence, and treatment of diseases. Decision trees are a critical tool in the accurate evaluation of biomedical data. Many applications, such as Weka, R, Rapid Miner, Knime, and Orange, use decision trees. In this study, classification was made with the C4.5 algorithm on biomedical data sets taken from the UCI Machine Learning repository. By analyzing the accuracy parameter, it was determined which application gave more accurate results [26].

Xia et al. discussed different indoor Wi-Fi positioning technologies, including various stages and processes of Wi-Fi fingerprint technology, and classified their methods used in various stages. In addition, they mentioned the publications and trends related to indoor location estimation made during the period when the study was published. They noted that there are still many potential areas for improvement in the field of indoor fingerprint positioning [27].

He et.al. in 2015 presented an overview of indoor positioning using Wi-Fi fingerprinting technology. This study aims to increase the precision of positioning by using various techniques such as collaborative localization, motion-assisted schemes, and system deployment strategies. It is suggested to combine Wi-Fi fingerprint signals with information received from motion sensors. It also mentions the adaptation of channel state information (CSI) to the estimation method. No experiment or simulation has been conducted on the performance of the methods mentioned in the article, but the achievements of previous studies are presented [28].

Zhou et al. introduced an indoor positioning system using Wi-Fi fingerprints that integrates a backpropagation neural network with an adaptive genetic algorithm alongside CSI tensor decomposition. They utilized a tensor decomposition approach based on the parallel factor (PARAFAC) analysis model and employed the iterative alternating least squares method. The results demonstrated that the system achieved levels of accuracy within 3m, 3.5m, and 4m, showcasing its reliability in measurements[29].

In this study, different machine learning methods are applied to the same data set, and their performance is compared. The database used is introduced in the next section. Additionally, the applied machine learning methods are explained and the way the data in the database is applied to machine learning is explained.

MATERIALS AND METHODS

Dataset Description

In this study, the performance of various machine learning methods in Wi-Fi fingerprint-based indoor location estimation was examined. For this purpose, a dataset was used that was presented in a recently published article namely "Supplementary open dataset for WiFi indoor localization based on received signal strength"[30]. In this study, the dataset is clearly explained. To create this database, data collection was carried out in 3 buildings. In this study, the data collected in the building presented with the HCXY code was studied. This building consists of offices at a college in Xuhhou City. The recordings were collected on the fourth floor of this building. The area of the fourth floor is about 3600m2. The floor plan is presented in Figure 1.

Figure 1
The 4th Floor Plan of the HCXY Building [30].

The corridor spans approximately 211 meters. Access Points (APs) with a single band were evenly set up in a symmetrical arrangement, placed at consistent heights, and spaced equally apart. They were installed on both sides of the corridor walls [30]. The points seen in the corridors in Figure 1 are the places where Wi-Fi RSSI values are taken. Some of these places are used for training and some for testing. For each measurement point, precise coordinates were recorded by using an electronic total station which has a 3mm error in 1km distance. At each training point, 30 records were taken. Additionally, for each test point, 10 records have been taken. The intersection of train points and test points is an empty set. There are 347 APs in the entire measurement area. Signals cannot be received from all of them at every point. RSSI data of APs from which signals are received are recorded in dBm units. These values are negative. The lowest signal level in the database is specified as -104. The value +100 was entered for APs where no signal could be received.

Some operations were performed on the data before starting to use it. First, the values of the APs without access, which were originally assigned as +100, were changed to -105, which is below the lowest value in the database, -104. Then, the average values of each of the 10 samples were taken. Thus, the effect of various interactions in the environment on RSSI was tried to be minimized. Before these operations, there were 11370 records in the training dataset and 860 records in the test dataset. After this process, 1137 records in the training dataset and 86 records in the test dataset were created.

Proposed Datamining Methods

In this study, the Orange Data Mining Tool was used in the application of the mentioned methods. After the existing database was loaded into the Orange application, all existing data mining algorithms were used in the application. The performance results of the six most successful methods are presented in this study. Details of these methods are mentioned below.

ANN: The Artificial Neural Network (ANN) operates as a forward-feeding model, effectively associating specified input sets with their corresponding outputs. This architecture consists of several layers, with each one linked to its successor. Every layer is comprised of neurons or processing elements, each equipped with a nonlinear activation function, excluding those at the input level. It incorporates a method of supervised learning known as backpropagation during the training phase. Unlike the traditional linear perceptron, the ANN model excels at identifying patterns within data that cannot be separated linearly [31], [32].

k-NN: The k nearest neighbor (k-NN) technique stands as a powerful tool within supervised machine learning, adept at handling both classification and regression challenges. It proves particularly efficient with smaller datasets and situations where class distinctions are clear-cut. In operation, the k-NN method calculates the distance between a new sample destined for classification and existing samples within the training set, employing the class attributes of the k^{th} closest neighbors to execute the classification. For determining the distance between the data requiring classification and the dataset used for training, it typically utilizes Euclidean, Manhattan, and Minkowski metrics, as outlined in the subsequent equations. In the context of regression, upon establishing the preferred distance metric, KNN proceeds to predict by identifying the nearest neighbors to the specific data point and then deducing the interpolations for the target values held by these neighbors. Here, selecting the ideal number for k emerges as a crucial step, significantly influencing the algorithm's effectiveness [31], [33].

Linear Regression: In tackling the issue of predicting a continuous variable Y based on multiple predictors $X_1,\ldots, X_p$, linear regression emerges as the simplest approach, modeling the dependent variable as a linear blend of the predictors. Its widespread use in various fields can be attributed to multiple factors. The ease with which its parameters can be understood is one such reason. Furthermore, the theoretical foundations of linear models are robust and mathematically sophisticated. Linear regression also serves as a foundational element for numerous contemporary analytical techniques. Particularly in situations where the dataset is small, or the signal strength is low, linear regression tends to offer a reasonable estimate of the relationship between the variables involved [34].

Decision Tree: The decision tree methodology stands as a renowned, extensively applied, and potent technique for classification tasks. Its superiority over alternative classification approaches lies primarily in the heightened clarity of the models it produces, alongside a more efficient evaluation process. Characterized by its nomenclature, this algorithm manifests in a tree-like structure, composed of both leaf and test nodes [35].

Random Forest: The Random Forest algorithm operates as a versatile machine learning technique, primarily leveraging both classification and regression trees, noted for its high efficiency, ease of use, and adaptability. As a member of the ensemble learning algorithms family, it utilizes the bagging approach. Its key strength lies in its ability to tackle both classification and regression challenges, foundational to numerous other machine-learning strategies. Comprising decision trees built simultaneously, Random Forest incorporates both classification and regression trees. Within each tree, nodes are segmented based on the most effective features, ensuring the attainment of the best possible solution from the available options [36].

Support Vector Machines: Fundamentally, a Support Vector Machine (SVM) exists as a computational tool, serving as a method for optimizing a certain mathematical function in relation to a specific set of data. The foundational principles of the SVM approach can indeed be outlined without delving into complex mathematical formulas. It is posited that comprehending the core of SVM classification requires an understanding of four principal elements: (i) the concept of a dividing hyperplane, (ii) the principle of a hyperplane with the widest margin, (iii) the notion of a soft margin, and (iv) the idea of a kernel function. Introduced by Cortes and Vapnik in 1995 and rooted in statistical theory, the SVM was designed to minimize the potential for error in general predictions by optimizing the space—or margin—around a dividing hyperplane, which in turn ensures the greatest possible separation between two distinct categories. This optimization requires that data points remain distanced from the hyperplane itself [37], [38].

Application of Machine Learning Algorithms

As it is known, the machine learning algorithms mentioned above have the ability to perform single-target regression. However, in the indoor location estimation process, both x and y coordinates need to be estimated. For this purpose, the relevant method for x and y coordinate estimation was trained separately. The results of the test data were obtained in this trained structure and the errors were calculated as RMSE.

All these operations were carried out on the Orange machine learning and data mining tool. Orange serves as a comprehensive suite for data analysis, leveraging machine learning and data mining via Python scripting and an intuitive visual programming interface. Structured as a hierarchical toolbox, it encompasses a variety of data mining elements. Foundational processes such as data filtering, assessing probabilities, and evaluating features form the base of this hierarchy and are integrated into more complex algorithms, including learning classification trees. This structure facilitates the seamless addition of new functionalities at various levels, enabling their integration with the current codebase [39].

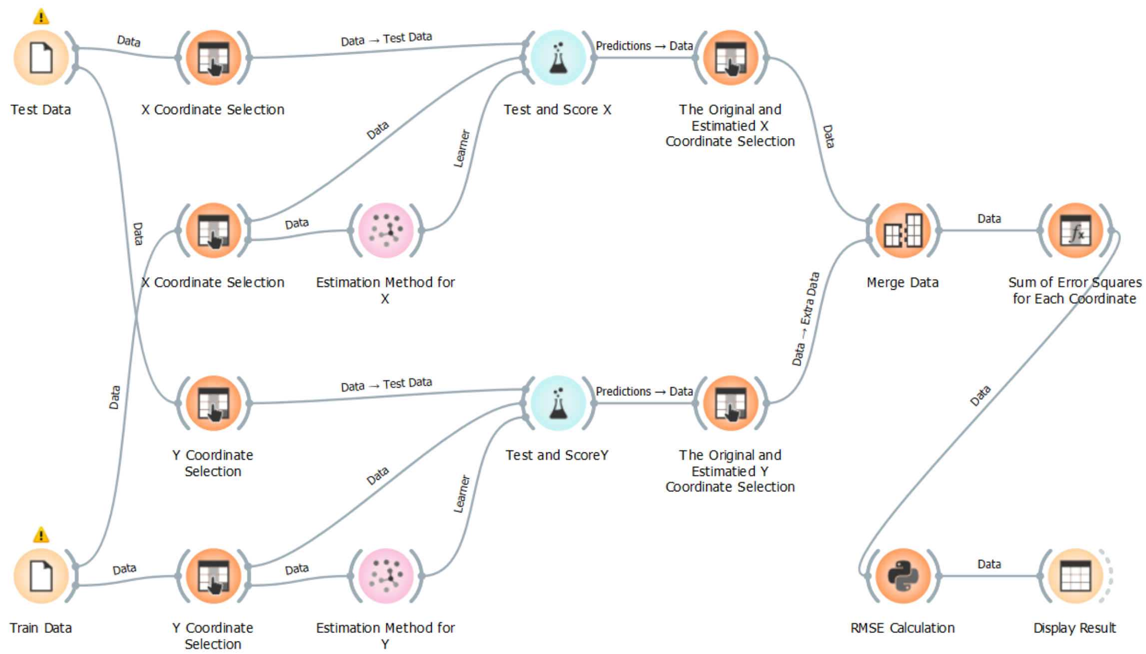

Figure 2
Flow Diagram of Machine Learning Methods over Orange Tool

First, the training data is divided into x and y targets. Two models of the same model were created, and training was provided by transferring x data to one of them and y data to the other. The test data was also divided into x and y and directed to the relevant model. To calculate RMSE data, the predictions created by the models and the original x and y values were taken from the test results and combined. Finally, RMSE was calculated with a Python script. A screenshot of the prediction structure created in the Orange tool for these operations is presented in Figure 2. The "Estimation Method" module shown in Figure 2 was changed for each machine learning method and results were obtained with the same structure.

RESULTS

Indoor location estimation using Wi-Fi fingerprinting is a very difficult process. Although these methods have been implemented in many studies, different methods may perform better for each different environment, depending on the characteristics of the environment. For this reason, different machine learning algorithms were examined for this data set and the results are given in Table 1.

Table 1
The RMSE Performances of Machine Learning Methods

	X COORDINATE RMSE	Y COORDINATE RMSE	OVERALL RMSE
ANN	5.8980 m	2.4480 m	6.3859 m
LINEAR REGRESSION	5.2320 m	3.1420 m	6.1027 m
K-NN	2.3090 m	1.6100 m	**2.8147 m**
DECISION TREE	12.4990 m	7.0110 m	14.3309 m
RANDOM FOREST	3.5250 m	2.4240 m	4.0444 m
SVM	5.9360 m	4.1920 m	7.2675 m

In the ANN used, 100 neurons were selected in the hidden layer. ReLU was chosen as the activation function. As seen in Table 1, ANN has an RMSE error of 5.4480m on the x-axis and an error of 2.4480m on the y-axis. The overall error in RMSE was determined as 6.3859m for ANN.

The performance of the linear regression model on this dataset was also examined. The prediction error of this method, as RMSE, was determined to be 5.230m in the x-axis direction, and the prediction error in the y-axis direction was 3.1420m.

The k-NN method was employed for location estimation with this dataset. The most successful performance belongs to this method. The neighborhood value determined here is determined as 5 for both the x estimator and the y estimator. Additionally, Euclidean distance was chosen as the distance metric. The RMSE error of this method in the indoor location estimation process made with the data in the database used was determined as 2.3090m on the x-axis and 1.6100m on the y-axis, as seen in Table 1. In general, the RMSE value is seen to be 2.8147m.

The decision tree has been the most unsuccessful or the method with the highest error among all the methods. Here, the error was determined as 12.4990m on the x-axis and 7.0110m on the y-axis. The overall error of this method was 14.3309m in RMSE.

The random forest algorithm was determined to be the most successful method after the k-NN algorithm. The random forest algorithm has an error of 3.5250m in its prediction on the x-axis and 2.4240m in its prediction on the y-axis. The general error was determined as 4.0444m. All errors are again calculated as RMSE.

The last method used for this process is SVM. Linear kernel was selected in SVM. It was observed that this method made an error of 5.9360m in the x-axis estimation and 4.1920m in the y-axis estimation. The overall error was determined as 7.2675m in RMSE. The parameters of the examined machine learning methods are presented in Table 2.

Each method displayed varying levels of accuracy in indoor location estimation. Notably, K-NN showed the best performance, while Decision Tree exhibited the highest error. Random Forest emerged as the second most successful method after K-NN. These findings underscore the importance of selecting appropriate algorithms tailored to specific environmental characteristics for effective indoor location estimation.

Table 2

The Fine-Tuned Parameters of Proposed Machine Learning Methods

	PARAMETERS	
ANN	Hidden Layer Neuron: Activation Function: Solver: Regularization: Max. Iteration:	100 ReLU Adam 0.0001 300
LINEAR REGRESSION	Regularization: Regularization strength: Elastic net mixing:	Ridge regression(L2) Alpha:1000 0.54:0.46
K-NN	Number of neighbors: Metric: Weight:	5 Euclidean Uniform
DECISION TREE	Min. number of instances in leaves: Do not split subsets smaller than: Limit the maximal tree depth to: Stop when majority reaches[%]:	2 5 100 95
RANDOM FOREST	Number of trees: Numb. of att. considered:	10 5
SVM	SVM Type: Regression cost (C): Complexity bound (v): Kernel: Iteration limit:	v-SVM 1.00 0.50 Linear 100

The results of our study and studies conducted with similar methods in the literature are given in Table 3. Although it is not possible to talk about the superiority of any method over the other because different databases are used, it is possible to list the methods that have consistently achieved a certain success among indoor location estimation methods as k-NN, ANN, Random Forest, SVM.

Table 3

Performance Comparison of Machine Learning Methods in Literature

STUDY	DATASET	OTHER METHOD/ERROR	NEURAL NETWORKS	RANDOM FOREST	SVM	K-NN
[19]	UJIIndoorLoc	Basic Indoor Location System/7.9m				
[20]	UJIIndoorLoc		ABC-ANN/1.0143m			
[21]	UWB/IMU	UWB-IMU/0.42m				
[29]			CSI-ANN/3.5m			
[22]	Self	Proposed/3.403m		4,889m	4,606m	3,902m
[23]	UJIIndoorLoc	WKNN/18.4m	CDAE-CNN/12.4m	15,9m		18,6m
[24]	Self	Smooting spline/9.38m		12,53m	13,75m	
[25]	Self		MLP/14.81m	3,5m	7,25m	5,255m
Proposed	HCXY college in Xuhhou City [30]		6.39m	4.04m	7.27m	2.81m

DISCUSSION AND CONCLUSIONS

In this study, the performance of Wi-Fi fingerprint-based indoor location estimation, which is frequently used due to the difficulty of using GPS signals in closed areas, was compared with different methods. Wi-Fi fingerprint-based location estimation methods appear as an important alternative for indoor location estimation due to the very low cost of additional hardware. However, since there will be no standard layout of APs, intensive preliminary work, and data collection are required for this process. In addition, it is predicted that Wi-Fi signals being affected by people in the environment reduce the location estimation consistency. Considering all these pros and cons, it is thought that this method can be useful in many areas such as the navigation of people in airports, hospitals, markets, etc. Future work could combine multiple machine learning algorithms to create a hybrid model that leverages the strengths of each method for better indoor location prediction accuracy. In addition, real-time indoor location estimation systems can be realized, which can provide instant and accurate location information by optimizing algorithms for efficiency and speed without compromising accuracy, and are supported by temporal filters since a continuous data flow is provided.

Ethical Statement

This study is an original research article designed and developed by the authors.

Author Contributions

Research Design M.Y. (%90) - M.F.U. (%10)

Data Collection M.F.U. (%90) - M.Y. (%10)

Research - Data Analysis - Validation M.F.U. (%70) - M.Y. (%30)

Writing the Article M.F.U. (%90) - M.Y. (%10)

Revision and Improvement of the Text M.F.U. (%80) - M.Y. (%20)

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