Gazi Üniversitesi
Fen Bilimleri Dergisi
PART C: TASARIM VE TEKNOLOJİ

Gazi University
Journal of Science
PART C: DESIGN AND TECHNOLOGY

GU J Sci, Part C, 13(3): 1331-1344 (2025)

Estimating Object Location in RF Communication by Using RSSI Values Through k-NN and Deep Learning Techniques

Nihat DALDAL[1*], Mohammed ZAIB[1]

[1]*Bolu Abant İzzet Baysal University, Department of Electrical and Electronics Engineering, BOLU, Turkey*

Article Info

Research article
Received: 24/05/2025
Revision: 23/07/2025
Accepted: 14/08/2025

Keywords

RSSI
RF Positioning
Object localization
Indoor localiziation
Outdoor localiziation
Wireless sensor networks

Makale Bilgisi

Araştırma makalesi
Başvuru:24/05/2025
Düzeltme: 23/07/2025
Kabul: 14/08/2025

Anahtar Kelimeler

RSSI
RF konumlama
Nesne konumlandırma
kapalı alan konumlandırma
açık alan konumlandırma
kablosuz sensor ağları

Graphical/Tabular Abstract (Grafik Özet)

This study investigates RF-based object localization using RSSI values with k-NN and deep learning. Indoor results show limited accuracy, while Neural Net Fitting achieves 94.05% outdoors, outperforming Machine Learning. Findings highlight challenges indoors and demonstrate NNF's effectiveness for reliable RF positioning in open-air environments. /Bu çalışma, k-NN ve derin öğrenme yöntemleri kullanarak RSSI değerleri ile RF tabanlı nesne konumlandırmayı araştırmaktadır. Kapalı alan sonuçları sınırlı doğruluk gösterirken, Neural Net Fitting açık alanda %94,05 doğruluk elde ederek Makine Öğrenmesini geride bırakmaktadır. Bulgular, kapalı alanlardaki zorlukları ortaya koymakta ve NNF'nin açık alan ortamlarında güvenilir RF konumlandırma için etkinliğini göstermektedir.

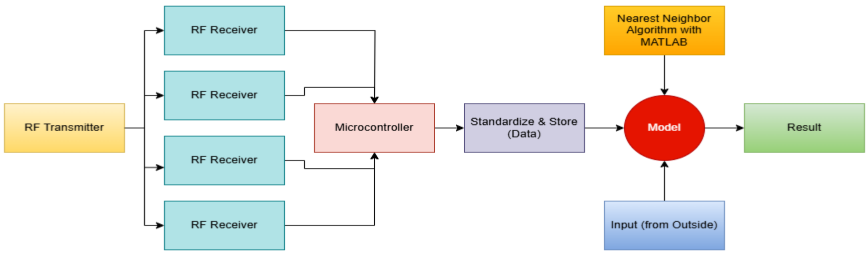


Figure A: *System block diyagram /* ***Şekil A:*** *Sistem blok diyagramı*

Highlights (Önemli noktalar)

- *In indoor environments, RSSI-based methods show low performance, with ANN achieving only 12%. / Kapalı alanlarda, RSSI tabanlı yöntemler düşük performans göstermekte, YSA ise yalnızca %12 başarı sağlamaktadır.*
- *In outdoor environments, Neural Net Fitting (NNF) achieved the best performance with 94.05% accuracy. /Açık alanlarda, Neural Net Fitting (NNF) %94,05 doğruluk ile en iyi performansı elde etmiştir.*
- *Results reveal that NNF provides a reliable and effective solution for RF-based localization in open areas. / Sonuçlar, NNF'nin açık alanlarda RF tabanlı konumlama için güvenilir ve etkili bir çözüm sunduğunu ortaya koymaktadır.*

Aim (Amaç): *This study aims to evaluate the effectiveness of RSSI-based methods, including k-NN and deep learning, for accurate object localization in indoor and outdoor environments. / Bu çalışma, k-NN ve derin öğrenme dahil olmak üzere RSSI tabanlı yöntemlerin, kapalı ve açık alanlarda nesnelerin doğru konumlandırılması için etkinliğini değerlendirmeyi amaçlamaktadır.*

Originality (Özgünlük): *This study uniquely compares k-NN, ANN, and Neural Net Fitting models for RSSI-based localization, highlighting their distinct performance differences in indoor and outdoor environments. / Bu çalışma, RSSI tabanlı konumlama için k-NN, YSA ve Neural Net Fitting modellerini özgün bir şekilde karşılaştırmakta ve bunların kapalı ve açık alanlardaki farklı performanslarını ortaya koymaktadır.*

Results (Bulgular): *The findings show that while indoor localization achieved limited accuracy (ANN 12%, MAE 66%), Neural Net Fitting reached 94.05% in outdoor environments, outperforming Machine Learning (74.4%).*

Conclusion (Sonuç): *Localization using RSSI signals becomes challenging indoors but provides superior accuracy in open areas. It serves as an alternative to GPS-based positioning./ RSS sinyalleri ile konum belirleme kapalı alanlarda zorlaşırken açık alanlarda üstün doğruluk sağlamaktadır. GPS konum belirlemeye göre bir alternatiftir*

*Corresponding author, e-mail: nihatdaldal@ibu.edu.tr
DOI: 10.29109/gujsc.1705341

GU J Sci, Part C, 13(3): 1331-1344 (2025)

Gazi Üniversitesi
Fen Bilimleri Dergisi
PART C: TASARIM VE TEKNOLOJİ

Gazi University
Journal of Science
PART C: DESIGN AND TECHNOLOGY

http://dergipark.gov.tr/gujsc

Estimating Object Location in RF Communication by Using RSSI Values Through k-NN and Deep Learning Techniques

Nihat DALDAL[1*], Mohammed ZAIB[1]

[1]Bolu Abant İzzet Baysal University, Department of Electrical and Electronics Engineering, BOLU, Turkey

Article Info

Research article
Received: 24/05/2025
Revision: 23/07/2025
Accepted: 14/08/2025

Keywords

RSSI
RF Positioning
Object localization
Indoor localiziation
Outdoor localiziation
Wireless sensor networks

Abstract

GPS-based positioning faces significant challenges in accuracy and reliability, especially due to environmental factors such as signal interruptions, multi-path propagation, and poor satellite visibility. This study explores using RF signal strength, or Received Signal Strength Indicator (RSSI) to estimate object positions, comparing different algorithms in indoor and open-air environments. For indoor localization, the Mean Absolute Error (MAE) algorithm achieved a limited 66% success rate, primarily due to RSSI fluctuations caused by signal reflections from obstacles. Similarly, when an Artificial Neural Network (ANN) is modeled for the indoor area, an efficiency rate of 12% is obtained. In open-air settings, Neural Net Fitting (NNF) outperformed Machine Learning (ML). NNF demonstrated high accuracy of approximately 94.05%, indicating effective learning and minimal overfitting. The ML model achieved 74.4% accuracy, showing less stability and overall accuracy compared to NNF. Results suggest NNF is more effective for RF-based localization, particularly in open-air environments where signal propagation is less complex.

RF Haberleşmesinde RSSI Değerleri Kullanılarak k-NN ve Derin Öğrenme Yöntemleri ile Nesne Konumunun Tahmin Edilmesi

Makale Bilgisi

Araştırma makalesi
Başvuru:24/05/2025
Düzeltme: 23/07/2025
Kabul: 14/08/2025

Anahtar Kelimeler

RSSI
RF konumlama
Nesne konumlandırma
kapalı alan konumlandırma
açık alan konumlandırma
kablosuz sensor ağları

Öz

GPS tabanlı konumlandırma, özellikle sinyal kesintileri, çoklu yol (multi-path) yayılımı ve zayıf uydu görünürlüğü gibi çevresel faktörler nedeniyle doğruluk ve güvenilirlik açısından önemli zorluklarla karşı karşıyadır. Bu çalışma, nesne konumlarını tahmin etmek için RF sinyal gücünü (yani Received Signal Strength Indicator (RSSI)) kullanmayı araştırmakta ve farklı algoritmaları kapalı alan ve açık hava ortamlarında karşılaştırmaktadır. Kapalı alan konumlandırmasında, Ortalama Mutlak Hata (MAE) algoritması, sinyallerin engellerden yansıması nedeniyle oluşan RSSI dalgalanmalarından ötürü %66 ile sınırlı bir başarı oranına ulaşmıştır. Aynı şekilde kapalı alan için Yapay Sinir Ağı (YSA) modellendiğinde verimlilik oranı %12 olarak elde edilmektedir. Açık hava ortamlarında ise Sinir Ağı Uydurması (NNF), Makine Öğrenimi'ne (ML) kıyasla daha iyi performans göstermiştir. NNF yaklaşık %94,05 gibi yüksek bir doğruluk oranı ile etkili öğrenme gerçekleştirmiş ve aşırı öğrenme (overfitting) göstermemiştir. ML modeli ise %74,4 doğruluk oranına ulaşarak NNF'ye kıyasla daha düşük kararlılık ve genel doğruluk sergilemiştir. Sonuçlar, sinyal yayılımının daha az karmaşık olduğu açık hava ortamlarında RF tabanlı konumlandırma için NNF'nin daha etkili olduğunu göstermektedir.

1. INTRODUCTION (GİRİŞ)

RF (Radio Frequency) modules are devices used to transmit and/or receive radio signals. They are generally used to provide a mode of communication through two or more devices [1]. A typical RF system consists of a transmitter and a receiver. The transmitter sends a radio signal through space, and a receiver receives that signal [2]. However, that signal doesn't reach the receiver with the same

*Corresponding author, e-mail: nihatdaldal@ibu.edu.tr
DOI: 10.29109/gujsc.1705341

power because it can get weak because of various factors like the distance between the transmitter and the receiver and the signal's frequency [3], [4].

RSSI (Received Signal Strength Indicator/Indicating) measures the power of the received signal [5]. In some RF modules, the weakness ratio of the signal through the RSSI pin can be seen. The RSSI pin has a voltage on it, which, on measuring, can be used to determine the power of the receiving signal [6]. If the voltage level of the RSSI pin is less than the normal value, it means the signal is not as strong as the transmitted signal. The voltage value of the signal can be changed to dBm (ratio between decibel value of the signal and 1 mV) to standardize the values.

In this modern world, every object's location can be detected through GPS (Global Positioning System). But the main disadvantage is that it can be very inaccurate and can misguide at several points, especially at indoor locations, due to signal interruptions, multipath propagation, and poor satellite visibility. To overcome this problem, in this study, the RSSI value feature of RF modules is used to determine the position of an object in an indoor and small space by transmitting a signal from the transmitter to the receiver and indicating the coordinates of the object by reading RSSI values.

2. LITERATURE REVIEW (LİTERATUR ARAŞTIRMASI)

There are several studies done on related topics. On reviewing them,

Du et al. have researched detecting the position of an object by using 16 L-shaped antennas, a 2 MHz RF signal receiver, and a non-parallel wave depth estimator (to infer the signal source's depth information by learning the sequence in the difference of phase). The method used there is detecting and measuring the Angle of Arrival (AoA) of the incoming signal by utilizing a custom Phase Difference Matching (PDM) algorithm. As a result, the system works with a median AoA error of 1.88 degrees vertically and 2.88 degrees horizontally, and the error determined in average depth estimation is 1.07m. [7]

Kleniatis et al. proposed a study on device-free localization (DFL) of a stationary human by using a few RFID antennas and large numbers of RFID tags. The authors reviewed two methods for this purpose, one of which employs group sparsity and RF propagation, and another one takes phase and rate fluctuations in visual notices them and uses them in the DFL Localization. [8]

Teeda et al. did research by using Unmanned Aerial Vehicles (UAVs) and ground Radio Frequency (RF) emitters. The main purpose of the project was to study the system performance for finding the point of RF emitters through measuring their Received Signal Strength Indicator (RSSI) values, which are derived from measuring signals done through UAVs. 2.4 GHz and 865 MHz, two unlicensed frequency bands, were used with interference to them, respectively. After conducting these experiments in rural areas, the results show that, with interference, the mean absolute localization error is 5 meters, while it is 4 meters without interference. [9]

Peled-Eitan et al. did research on the localization of a handset user by detecting their RF transmitted signals and measuring their RSSI values. Two types of algorithms, weighted mean and Extended Kalman Filter (EKF), are used. Unattended static and moving transceiver nodes were used to simulate the environment. Several maneuvers were simulated to test and check both algorithms in different-shaped simulated urban environments. Results show that the EKF algorithm has the lowest position estimation error. [10]

Chen et al. proposed a study on using an RL2 robotic system to detect the position of an object by using UHF Radio-Frequency Identification (RFID) tags. The robot has mounted reader antennas for accurate and speedy localization through a reinforcement-learning-based RL (Reinforcement Learning) trajectory optimization network. By evaluating the results, it is noticed that the median 3D localization accuracy is 0.55 m, and its speed of finding different RFID tags is 2.13x faster than the baseline. [11]

3. METHODOLOGY (YÖNTEMLER)

In this study, two datasets have been used to determine the position of the object, one for indoor localization, which has walls on the sides (which causes noise in the values), and another one in open air. All of these measurements and calculations have been done in the light of the Friis transmission equation (Equation 1). The Friis transmission equation is a fundamental formula used in telecommunications engineering to calculate the power received by one antenna when another antenna transmits a known amount of power at a certain distance under ideal conditions (free space propagation).

$$P_r = P_t . G_t . G_r . \left(\frac{\lambda}{4\pi d}\right)^2 \quad (1)$$

Where P_r is the power received by the receiving antenna (in Watts), P_t is the power transmitted by the transmitting antenna (in Watts), G_t is the gain of the transmitting antenna (dimensionless, often expressed in dBi), G_r is the gain of the receiving antenna (dimensionless, often expressed in dBi), λ is the wavelength of the transmitted signal (in meters), and d is the distance between the transmitting and receiving antennas (in meters). The result values, from the Friis transmission equation, have then been changed into dBm values with the following formula (Equation 2):

$$\text{dBm} = 20 \log \left(\frac{received\ signal\ voltage\ (V)}{1\ mV}\right) \quad (2)$$

Details for both datasets and different models are as follows:

3.1. Data Collection System (Veri Toplama Sistemi)

RSSI measurement can be done with different methods. One of these methods is connecting a voltmeter to the RSSI output pin of the receiver RF module, and the voltage is noted. Another method is to use a microcontroller in place of a voltmeter, which is programmed to read the RSSI value from the RF modules and pass it to the computer. In this study, units with integrated RF modules, positioned at the corners, measure Received Signal Strength Indication (RSSI) values via the microcontroller's analog port and wirelessly transmit these readings, along with unit identification, to a central data acquisition unit (as depicted in Figure 1). The central data acquisition unit receives the RSSI values from the corner-mounted units (as shown in Figure 2) via the RF module and transmits them to a computer.

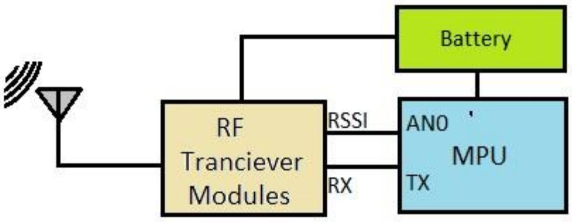


Figure 1. RSSI Measurement System placed in the corners (Köşelere yerleştirilen RSSI Ölçüm Sistemi)

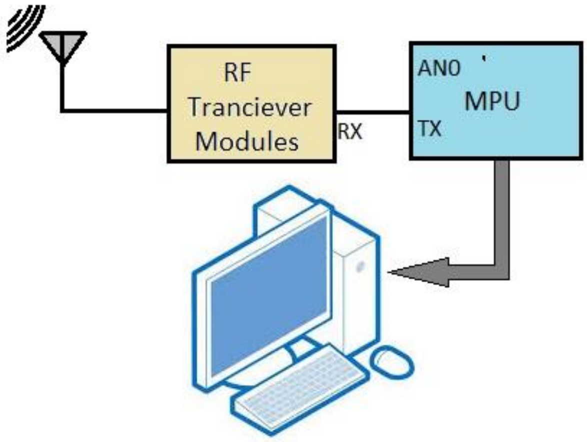


Figure 2. RSSI value data collection system (RSSI sinyali veri toplama sistemi)

4. INDOOR LOCALIZATION (KAPALI ALAN KONUMLAMA)

In this part of the study, there are several steps, like collecting values from the indoor measurement area, processing the values, using the MATLAB Algorithm for Mean Absolute Error (MAE) ((nearest neighbor in simple words) (should not be confused with k-NN Algorithm)) model, and then analyzing the results. The block diagram for the study is shown in Figure 3.

All the steps are described below with details.

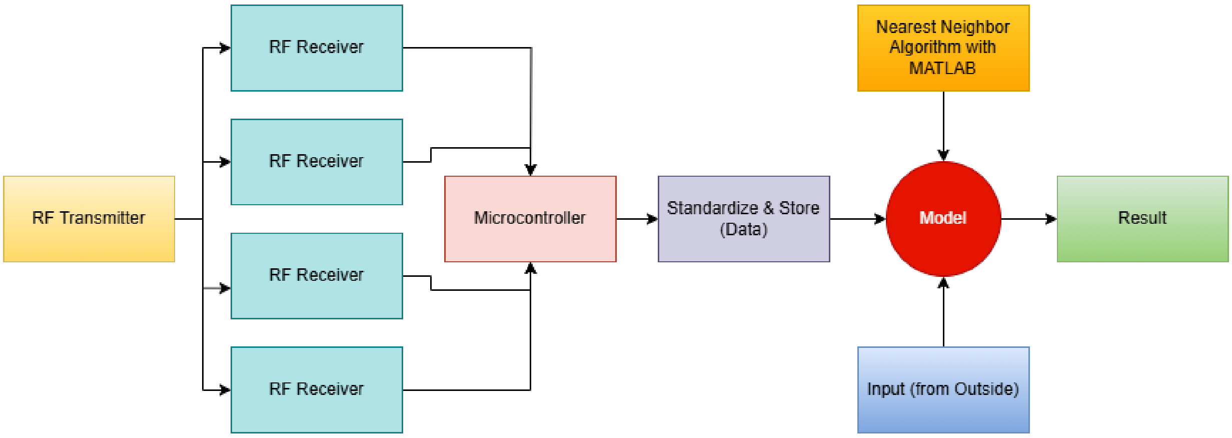


Figure 3. Block diagram for ındoor localization (Kapalı alan konumlama blok diyagramı)

4.1. Indoor Collecting the data (Kapalı Alanda Veri Toplama)

The dataset for this part of the study was collected from a 5x6 meter area, which is an indoor area with walls on every side, as shown in Figure 4a. Four RF receivers have been placed in every corner of the area to receive the signal from the RF transmitter, which is mobile in the area of measurement, wandering from point to point, as shown in 4b. A microcontroller is used to calculate the RSSI values of the received signals from RF receivers and save them. The resultant matrix is 25x4, with 25 values from all four corners.

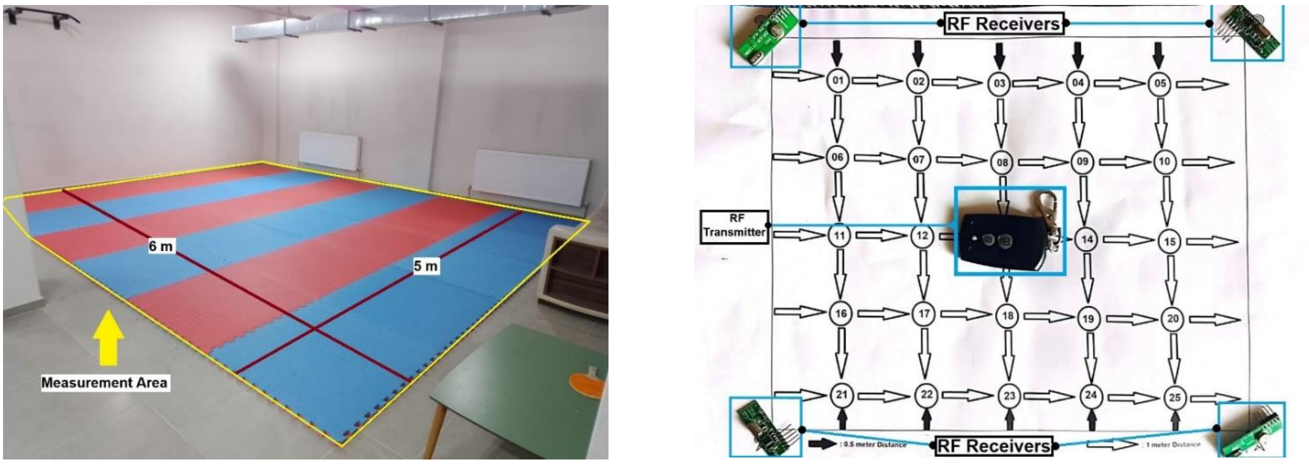


Figure 4. a. Measurement Area b. Layout for Indoor Localization with 4 Receivers and 1 Transmitter

(a.Ölçüm alanı b. Kapalı alanda 4 alıcı 1 verici ile yerleşim modüllerin düzeni)

Table 1 shows the values (in dBm) taken from the first five points for all four receivers. These first five points are selected as an example to show how non-linearly RSSI values fluctuate while measuring indoors due to the noise and reflection of RF signals.

Table 1. First 5 points (dBm) (İlk 5 nokta değerleri)

Point No.	1st Receiver	2nd Receiver	3rd Receiver	4th Receiver
01	65.1295	61.8684	64.0814	61.6915
02	64.4803	64.0005	63.9731	62.7344
03	65.3434	63.7504	63.8902	64.2968
04	64.5577	62.8290	63.2870	64.1095
05	63.6082	63.9179	63.8066	64.8359

4.2. Indoor Position Estimation (Kapalı Alanda Konum Tahmini)

In this study, two algorithms are used to determine the position of an object transmitting RF signals on a specific layout and then compared. One of these algorithms is Mean Absolute Error (MAE), which is also known as k-NN. The other one is Artificial Neural Network (ANN). The details of these algorithms and the results are as below:

4.3 MAE Algorithm (MAE Algoritması)

In this part of the study, the Mean Absolute Error (MAE) algorithm is used. The reason for using this algorithm is that it uses a simple algorithm of subtraction, while no model needs to be trained. From the dataset, a 25x4 matrix is used as the main matrix. A MATLAB code is written in which fresh readings from all four receivers are taken as input as a 1x4 matrix and compared with the main matrix, all rows, one-by-one, to find the nearest match. Code finds the difference between every element from the same column, and it applies to all rows, with the column remaining constant. The output is the row with the least element-wise average difference, and that row number is the point number of that object in the layout, as shown in .. The block diagram of Nearest Neighbor (or MAE) is shown in Figure .

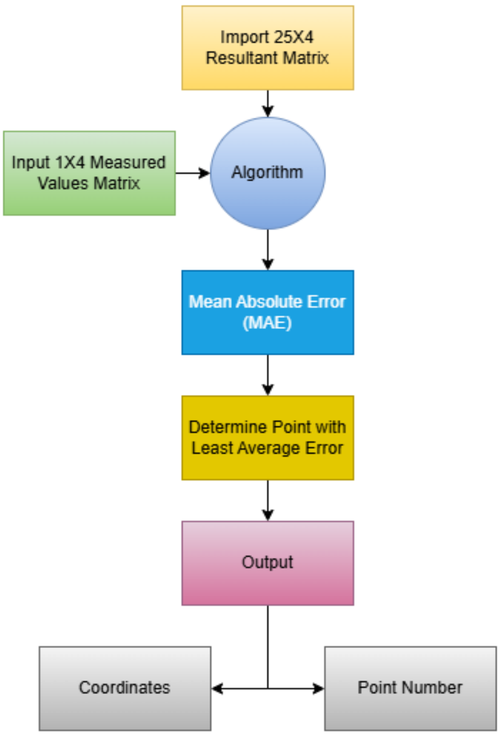


Figure 5. MAE algorithm block diagram (MAE algoritma blok diyagramı)

For testing the algorithm, two more values were taken from these same points to compare it with the main matrix. As a result, 33 out of 50 checks gave an accurate result.

Success rate % = (33 / 50) * 100 = 66%

So, the success rate of the model is 66%. This performance is not very good for a localization system. The reason for this performance is that RSSI values, taken from different points, do not change with sequence but randomly because of reflecting RF signals from obstacles, which act as noise for the system.

4.4 Artificial Neural Network (ANN) Algorithm (Yapay Sinir Ağı (YSA) Algoritması)

In this part of the study, the Artificial Neural Network (ANN) algorithm is used. From the dataset, a 25x4 matrix is used as the main matrix, same as MAE. A MATLAB application, Neural Net Fitting, is used to determine the relation between inputs and outputs. The 25x4 matrix, which has RSSI values taken from all points for all four receivers, has been taken as predictors, and a 25x1 matrix, with position values, has been taken as responses. The data splits as 70% for training and 15% for validation, while the remaining 15% is used to test the algorithm. 10 neural layers are used, which are hidden inside the neural network. The neural network is trained by the Scaled Conjugate Gradient algorithm, which is a memory-efficient algorithm with respect to Bayesian Regularization and Levenberg-Marquardt. The result of the training of the neural network is given in

Table 2.

Table 2. Artificial neural network (ANN) algorithm

	Observations	MSE	R
Training	17	26.6850	0.6843
Validation	4	31.1991	0.9441
Test	4	101.5748	-0.4053

(Yapay sinir ağı (YAS) algoritması)

For a better result, the Mean Squared Error (MSE) should be near 0, and the square of R (R^2) should be near or equal to 1. As shown in

Table 2, R^2 is smaller than 1 (even negative in the test), and MSE is much larger than 0, which is not a good and efficient result, and it means that the model is not trained very well and performs badly. More detail about the neural training is mentioned in Table 3.

Table 3. Training details for neural network
(Sinir ağı için eğitim detayları)

Unit	Initial Value	Stopped Value	Target Value
Epoch	0	8	1000
Elapsed Time	-	00:00:00	-
Performance	196	12.1	0
Gradient	7.35E+05	2.3	0
Mu	679	21.7	1.00E-06
Validation Checks	0	6	6

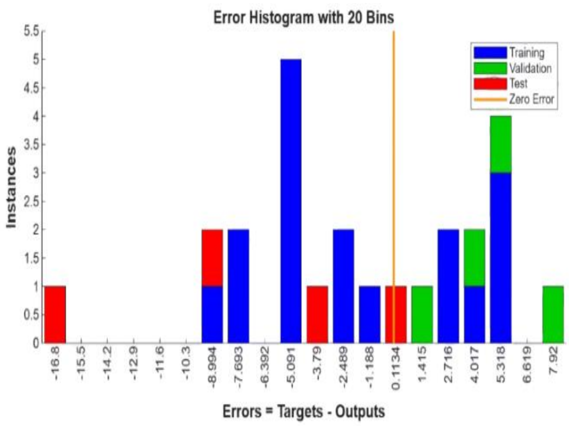


Figure 6. Error histogram for artificial neural network (Yapay sinir ağı için hata histogramı)

6 shows an error histogram for an Artificial Neural Network, showing the distribution of "Errors = Targets - Outputs" across 20 bins.

Blue bars represent training errors, green are validation errors, and red are test errors. The orange line marks zero error. The plot helps assess model performance by showing how frequently different error magnitudes occur for each data subset.

The histogram shows a high frequency of errors clustered around zero, with the highest bar being 5 instances, but not on the 0-error line. The Errors axis spreads from -16.8 to 7.92. It means that the model is not trained very well, and the result is not accurate accordingly.

	Observations	MSE	R
Training	17	26.6850	0.6843
Validation	4	31.1991	0.9441
Test	4	101.5748	-0.4053

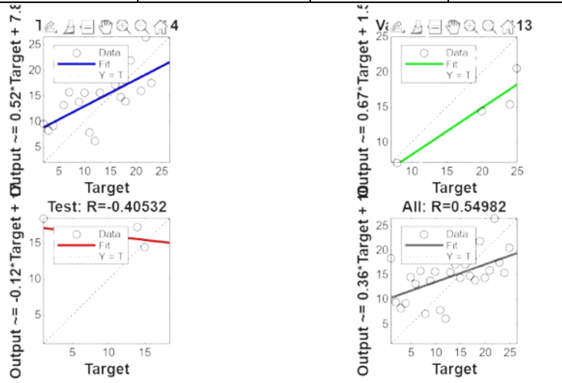


Figure 7. Regression graph (Regresyon grafiği)

Figure is a regression graph. Here, it can be seen that the target curve is not aligned with the result curve very well, but is scattered for all the data types (training, validation, and test).

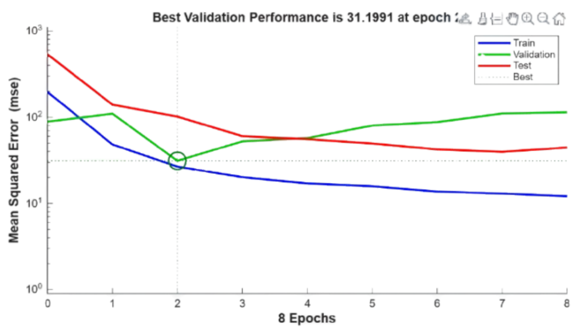


Figure 8. Performance plot (Performans grafiği)

In Figure 8, the Performance Plot, it can be seen that epoch 2 has the best performance, with Mean Square Error (MSE) rate is 31.1991.

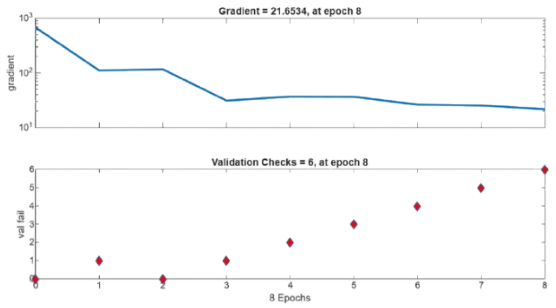


Figure9. Gradient and validation check plot (Gradyan ve doğrulama kontrol grafiği)

Figure shows the gradient and validation check plots for 8 epochs, where the gradient is 21.6534 and the validation check is 6. In summary, the results presented in these figures indicate a bad performing predictive model with low accuracy, weak generalization, and unstable convergence during training.

According to the histogram, when a threshold of ±1 is given and the instances are counted that fall in the correct result category, it can be observed that the bins from approximately -1.188 to +1.415 fall within this range. 3 out of 25 instances are giving a more approximate result. After calculating with the following formula:

Success Rate % = (3 / 25) * 100 ≈ 12%

The success rate for the model of Artificial Neural Network (ANN) is approximately 12%.

5. OUTDOOR LOCALIZATION (AÇIK ALAN KONUMANDIRMA)

This part of the study consists of several steps, like collecting values from the open-air measurement area, processing the noted values, preparing Machine Learning (ML) and Neural Net Fitting (NNF) (in MATLAB) models, and then testing the results. The block diagram for the study is as shown in

Figure .

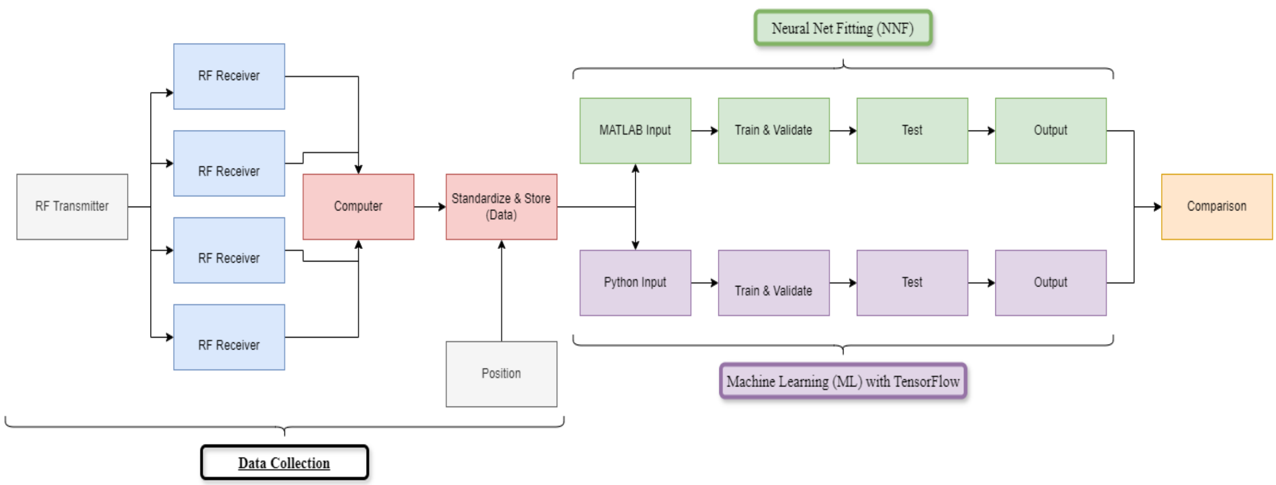
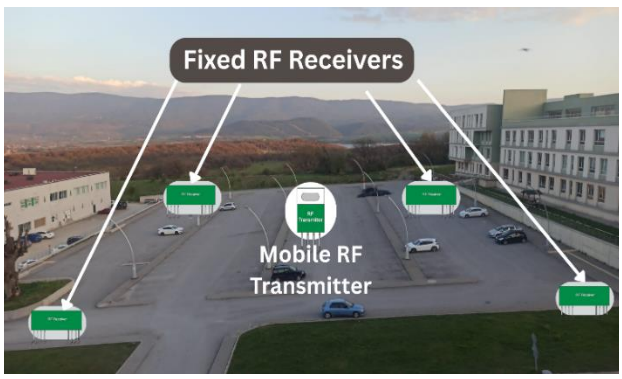


Figure 10. Block diagram for open-air localization (Açık alan veri toplama sistemi blok diyagramı)

5.1. Outdoor Collecting the Data (Açık Alanda veri Toplama)

The data, which is used in the study, is collected for an open-air parking lot, and the dimensions for the measurement area are 50x50 meters. Figure shows the parking lot, which has been taken as a reference. Regarding that area, a MATLAB program is written, which gives the dBm results of every point on that 50x50 m area with 2-meter distances



between every point in both directions, respectively. Figure 1 and Figure 2**Hata! Başvuru kaynağı bulunamadı.** show the RSSI Measurement System (placed in the corners) and RSSI value data collection system, respectively. That MATLAB program has been written in light of the Friis transmission equation, and a small amount of noise has been added to simulate the real working of algorithms.

Figure 11. Test area for outdoor measurement (Açık alan ölçüm test alanı)

As a layout, each corner of all four corners has an RF receiver that receives the RF signal, which is transmitted by an RF transmitter on the measurement point [12]. The area consists of 672 points (due to a distance of 2 meters between every point). Figure shows the measurement area layout and the places where the RF transmitters and receivers are located in that layout as a sample.

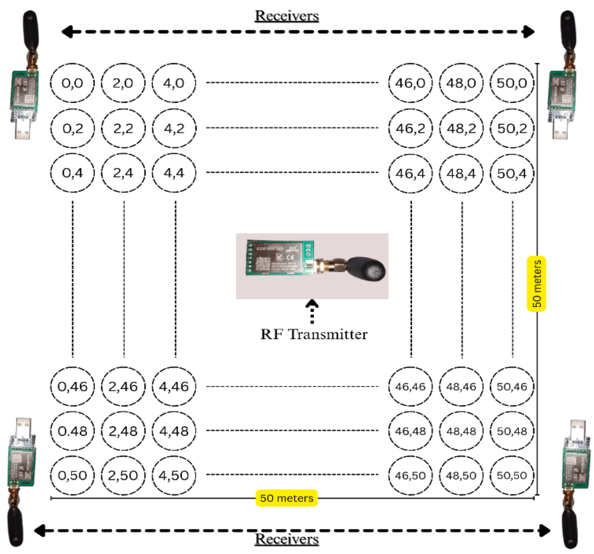


Figure 12. Layout for open-air localization with 4 receivers and 1 transmitter (4 alıcı ve 1 verici ile açık alan konumlandırma düzeni)

The RF transmitter, present on the spot (measurement point), transmits an RF signal, which is received by all four receivers that are present on the corners with coordinates of (0,0), (50,0), (0,50), and (50,50) with a voltage value, and then this received signal voltage value (rV) is changed into dBm to standardize it with the following formula:

$$\text{dBm} = 20\ log(\frac{received\ signal\ voltage\ (rV)}{1\ mV})$$

After standardization, the received values (in dBm) are stored in an Excel sheet to use for further steps and processes in different models. [13]

5.1. Models and Applications (Model ve Uygulamalar)

In this study, two models are used to determine the position of an object transmitting RF signals on a specific layout and then compared. One of these models is Neural Net Fitting, which is a toolbox in MATLAB [14]. The other one is Machine Learning, by TensorFlow (a library in Python) [15]. Both models find a relation between inputs and outputs and train their algorithms by neural networks [16]. The reason these models are used is to study the behavior of different neural networks with different types of RSSI values. Also, these models perform very well with nearly linear values, unlike in an indoor scenario, where values have quite a nonlinear difference. The details of these models and the results are as below:

5.2. Neural Net Fitting Algorithm (NNF) (NNF Algoritması)

The retrieved values, stored in an Excel sheet, were imported into MATLAB as an input matrix with 4 columns of data for every row out of all 672 rows and became a 672x4 matrix. An output matrix with 1-to-672 numbers and a 672x1 dimension was formed to relate it to the input matrix. The input matrix has a nearly non-linear difference between different points. These 672x4 input and 672x1 output matrices make a dataset.

To model the dataset's complicated, nonlinear interactions, neural network regression was used. Specifically, the MATLAB Neural Net Fitting App (launched with the nftool command or through the Machine Learning and Deep Learning toolboxes) was used to provide an interactive environment for training and testing shallow, two-layer feedforward neural networks. This method aided in the creation of a prediction model capable of capturing complex patterns and producing reliable estimates.

The 672x4 matrix, which has RSSI values taken from all points for all four receivers, has been taken as predictors, and a 672x1 matrix, with position values, has been taken as responses. The data splits as 70% for training and 15% for validation, while the remaining 15% is used to test the algorithm. 10 hidden neural layers are used. The neural network is trained by the Levenberg-Marquardt algorithm, which is a fast algorithm with respect to Bayesian

Regularization and Scaled Conjugate Gradient. The result of the training of the neural network is given in Table 4

Table 4. Results of neural network training (Sinir ağı eğitim sonuçları)

	Observations	MSE	R
Training	470	0.0126	1.0000
Validation	101	0.0282	1.0000
Test	101	0.0321	1.0000

That's why R being equal to 1 indicates good training of the model. More detail about the neural training is mentioned in Table 5.

Table 5. Details for neural training (Ağ eğitim detayları)

Unit	Initial Value	Stopped Value	Target Value
Epoch	0	194	1000
Elapsed Time	-	00:00:01	-
Performance	1.92E+05	0.0123	0
Gradient	7.35E+05	2.3	1.00E-07
Mu	0.001	0.01	1.00E+10
Validation Checks	0	6	6

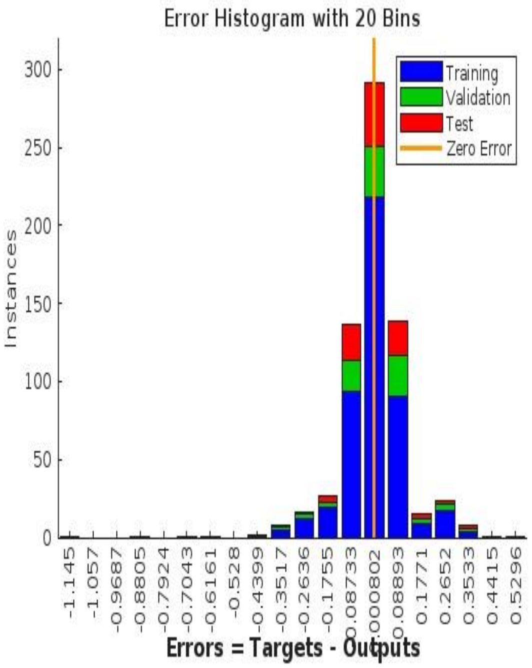


Figure 13. Error histogram (Hata diyagramı)

For a better result, the Mean Squared Error (MSE) should be near 0, and the square of R (R^2) should be near or equal to 1. As shown in Table 4, R^2 is 1 and MSE is close to 0, which is a great result, and it means that the model is trained very well. R being equal to 1 may be seen as an indicator of overfitting, but in some scenarios where data has a very linear approach, R values can be exactly 1. In this study, the values have a linear approach, as it is a simulated model with noise.

Hata! Başvuru kaynağı bulunamadı. presents the distribution of prediction errors. The histogram shows a high frequency of errors clustered around zero, with the highest bar exceeding 270 instances, indicating that the model frequently makes very accurate predictions. However, the distribution also exhibits a spread, with errors ranging from approximately -0.3 to 0.35, suggesting that while the model is generally accurate, there are instances of larger prediction errors. Overall, the concentration of errors near zero is a positive sign, indicative of good model performance.

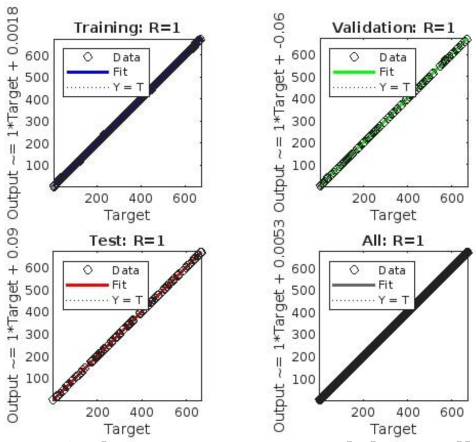


Figure 5. (a-d), "Training, test, validation,all R=1" ,(Eğitim, test, doğrulama ve bütün teslerde R=1)

Figure **5** illustrates the relationship between the model's output and the target values across different datasets. In each plot, the data points align closely with the line "Y=T," representing perfect prediction, and are well-fitted by a linear regression line. The equations provided within each plot, slopes are very close to 1 (approximately 1), and small intercepts (ranging from -0.06 to 0.09) demonstrate a strong linear correlation and minimal bias. This strong alignment suggests excellent predictive capability across training, test, and validation sets, indicating that the model generalizes well.

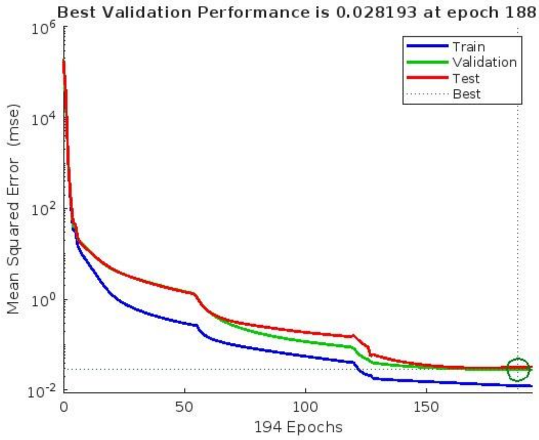


Figure 6. MSE value (MSE değeri)

Figure 65 displays the mean squared error (MSE) for the training, validation, and test sets as a function of training epochs. The MSE decreases rapidly in the early epochs and stabilizes at a low value, with the best validation performance recorded as 0.028193 at epoch 188. The convergence of the MSE to a low plateau is a favorable outcome, demonstrating effective learning and a stable model.

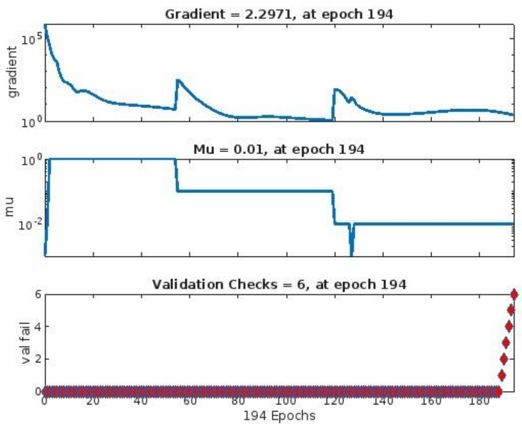


Figure 7. Validation (Doğrulama)

Figure 7 provides details on validation metrics at the optimal epoch (194). The gradient is 2.2971, mu is 0.01, and the validation checks reached 6. These values offer insight into the training process; a stable gradient and mu, along with the validation checks, suggest that the training process converged appropriately and the model's performance is reliable.

In summary, the results presented in these figures indicate a well-performing predictive model with high accuracy, strong generalization, and stable convergence during training.

According to the histogram, when a threshold of ±1 is given and the instances are counted that fall in the correct result category, it can be observed that the bins from approximately -0.17 to +0.17 fall within this range. 632 out of 672 instances are giving a more approximate result. After calculating with the following formula:

Success Rate % = (632 / 672) * 100 ≈ 94.05%

The success rate for the model of Neural Net Fitting (NNF) is approximately 94.05%.

5.3. Machine Learning Algorithm (ML) (Makine Öğrenmesi Algoritması)

In this study, as an input, a 672x4 matrix, and as an output, a 672x1 matrix are taken as the dataset, similar to the Neural Network Model. This dataset is used to train a Machine Learning (ML) model, implemented using the TensorFlow Python library. The model aims to learn a functional relationship between the four input features and the single output variable. The structure of the input and output matrices represents a dataset where each of the 672 samples is characterized by four distinct features and a corresponding target value. Utilizing TensorFlow's capabilities, a customized model was constructed to capture the underlying patterns and dependencies within this data. The objective is to develop a predictive model capable of accurately estimating the output for new, unseen input data. This process, facilitated by TensorFlow's robust computational graph and automatic differentiation features, allows for the efficient training and optimization of the model.

For training the model, various numbers of epochs were used to find the behavior of the algorithm for the training of the model. First of all, 100 epochs were used to train the model. When the result was not satisfactory, the number of epochs was increased to analyze the behavior of the algorithm. 200, 500, 1000, and 2000 epochs were applied. The minimum values of loss, Mean Absolute Error (MAE), validation loss, and validation Mean Absolute Error (MAE) are as shown in Table 6 for all epoch numbers.

Table 6. Model properties for different epochs (Farklı denemelerde model özellikleri)

By analyzing data from Table 6, we understand that the training of the model demonstrates a clear inverse relationship between epochs and both loss and mean absolute error on the training set, indicating a progressive enhancement in the model's capacity to fit the training data. Concurrently, the validation metrics also exhibit a general trend of decline; however, the presence of fluctuations suggests a degree of instability in the model's generalization across unseen data. These observations imply that while the model is learning, scrutiny of the validation set is warranted to ascertain the consistency of its performance.

When the algorithm runs with 2000 epochs, for every epoch, the graphic data is as in the following figures (Figure 8 and Figure 9):

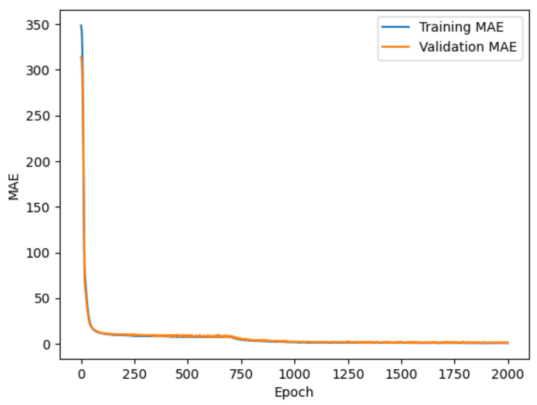


Figure 8. Mean absolute error (MAE) (Ortalama .)

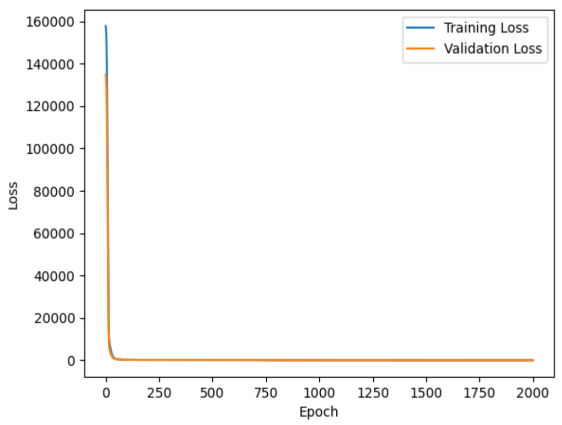


Figure 98. Loss/mean squared error (MSE) (MSE hatası)

In Figure 8 and Figure 9, it can be seen that, when the model training is started, in the beginning, Mean Absolute Error (MAE) gradually decreases and nearly comes to zero at 2000 epochs. For loss, it suddenly drops down to near zero in some initial epochs, and continues its journey, nearing zero. It is valid for both training and validation data. From this, we understand that, number of epochs should be high in number, but it should be limited to avoid overfitting.

For testing the accuracy of the model, the input matrix is used as test data. After analyzing the result, 500 out of 672 points were located correctly with a threshold of ±1. The success rate for the model:

Success Rate % = (500 / 672) * 100 ≈ 74.4%

So, the success rate for Machine Learning (ML) is approximately 74.4%.

6. RESULT AND DISCUSSION (SONUÇ VE TARTIŞMA)

Epochs	Loss	MAE	Validation Loss	Validation MAE
100	244.8224	12.2683	240.5026	11.7979
200	148.1362	9.5236	185.2436	10.0742
500	103.1991	7.0606	148.9660	9.1403
1000	6.8923	1.9481	11.4637	2.3249
2000	1.4637	0.9244	4.8948	1.4838

This study investigated the effectiveness of different approaches for estimating object positions using RF signal strength (RSSI) in both indoor and open-air environments. For indoor localization, the Mean Absolute Error (MAE) algorithm demonstrated a limited success rate of 66%. While the Artificial Neural Network (ANN) algorithm demonstrates a much smaller success rate of as small as 12%. This outcome reveals the challenges of indoor RF-based localization, primarily due to RSSI fluctuations caused by signal reflections from obstacles like walls, which introduce significant noise and unpredictability into the measurements. This suggests that the MAE and ANN algorithms are not robust enough to handle the complexities of indoor RF signal propagation.

In contrast, for open-air localization, the Neural Net Fitting (NNF) model significantly outperformed the

Machine Learning (ML) model. The NNF model achieved a high success rate of approximately 94.05%, supported by strong performance metrics: low Mean Squared Error (MSE) values (0.0126 for training, 0.0282 for validation, and 0.0321 for testing) and R values of 1 across all datasets. These results indicate that NNF effectively captures the complex, non-linear relationships between RSSI values and object positions in open-air settings. The consistency of the model's performance across training, validation, and test sets suggests good generalization and a low risk of overfitting.

The Machine Learning model, implemented using TensorFlow, achieved a success rate of 74.4%. While the model's performance improved with increased training epochs, it exhibited less stability and overall accuracy compared to the NNF model. This suggests that while machine learning techniques can be applied to RF-based localization, the specific architecture and training process are critical for achieving optimal results. The fluctuations observed in the validation metrics imply that careful tuning and regularization are necessary to ensure the model generalizes well to unseen data.

Results for different studies and methods are compared to the current study in Table **7**.

Table 7. Comparison of different studies (Farklı çalışmalar ile karşılaştırma)

Study	Method	Result (Accuracy)
Du et al. [7]	Angle of Arrival (AoA)	87.71%
Kleniatis et al. [8]	RFID	80%
Teeda et al. [9]	RSSI	93.22%
Peled-Eitan et al. [10]	RSSI	90%
Chen et al. [11]	RFID	90.83%
Ferrero-López et al. [13]	Bluetooth Low Energy (BLE)	90.80%
Current Study	MAE	66%
	ANN	12%
	NNF	94.05%
	ML	74.4%

To build upon these findings, future research should prioritize enhancing accuracy and robustness, particularly in indoor environments. This involves exploring more sophisticated algorithms or hybrid approaches, investigating advanced deep learning architectures like CNNs or RNNs, and incorporating additional sensor data. Analyzing and mitigating the impact of environmental factors on RSSI values and extending the research to real-time applications are also important directions.

6. CONCLUSIONS (SONUÇLAR)

This study evaluated RF-based object localization using RSSI values and different algorithms. The Mean Absolute Error (MAE) and Artificial Neural Network (ANN) algorithms demonstrated limited accuracy in indoor environments, likely due to RSSI variability caused by signal reflections.

In open-air settings, Neural Net Fitting (NNF) outperformed Machine Learning, achieving higher accuracy in position estimation. Specifically, NNF achieved a success rate of approximately 94.05%, while Machine Learning reached 74.4%. These studies suggest that neural network models, particularly NNF, are more effective for RF-based localization, especially in open environments where signal propagation is less complex.

DECLARATION OF ETHICAL STANDARDS (ETİK STANDARTLARIN BEYANI)

The author of this article declares that the materials and methods they use in their work do not require ethical committee approval and/or legal-specific permission.

Bu makalenin yazarı çalışmalarında kullandıkları materyal ve yöntemlerin etik kurul izni ve/veya yasal-özel bir izin gerektirmediğini beyan ederler.

AUTHORS'CONTRIBUTIONS (YAZARLARIN KATKILARI)

Nihat DALDAL: Designed and implemented the systems to obtain the required measurement values from RF modules based on distance and conducted studies on position estimation using the measured RSSI data.

Mesafe bazlı olarak RF modüllerinden gerekli ölçüm değerlerini elde etmek için sistemleri tasarladı ve uyguladı, ayrıca ölçülen RSSI verilerini kullanarak konum tahmini üzerine çalışmalar yürüttü.

Mohammed ZAIB: Collected RSSI data from the deployed systems and contributed to position estimation studies.

Kurulan sistemlerden RSSI verilerini topladı ve konum tahmini çalışmalarına katkıda bulundu.

CONFLICT OF INTEREST (ÇIKAR ÇATIŞMASI)

There is no conflict of interest in this study.

Bu çalışmada herhangi bir çıkar çatışması yoktur.

REFERENCES:

[1] M. Feng, S. C. Shen, D. C. Caruth, and J. J. Huang, "Device technologies for RF front-end circuits in next-generation wireless communications," *Proceedings of the IEEE*, vol. 92, no. 2, pp. 354–374, 2004, doi: 10.1109/JPROC.2003.821903.

[2] B. Clerckx, R. Zhang, R. Schober, D. W. K. Ng, D. I. Kim, and H. V. Poor, "Fundamentals of wireless information and power transfer: From RF energy harvester models to signal and system designs," *IEEE Journal on Selected Areas in Communications*, vol. 37, no. 1, pp. 4–33, 2019, doi: 10.1109/JSAC.2018.2872615.

[3] Y. Zeng, B. Clerckx, and R. Zhang, "Communications and Signals Design for Wireless Power Transmission," *IEEE Transactions on Communications*, vol. 65, no. 5, pp. 2264–2290, 2017, doi: 10.1109/TCOMM.2017.2676103.

[4] A. A. Abidi, "Low-power radio-frequency IC's for portable communications," *Integrated Circuits for Wireless Communications*, vol. 83, no. 4, pp. 3–28, 1998, doi: 10.1109/9780470544952.ch1.

[5] D. N. Purnamasari and M. Ulum, "LoRa 920 MHz as a Green Technology in Maritime Education : Optimizing Modulation Settings for Real-Time Environmental Data," vol. 05004, 2024.

[6] P. D. P. Adi and A. Kitagawa, "A performance of radio frequency and signal strength of LoRa with BME280 sensor," *TELKOMNIKA (Telecommunication Computing Electronics and Control)*, vol. 18, no. 2, pp. 649–660, Apr. 2020, doi: 10.12928/TELKOMNIKA.V18I2.14843.

[7] T. Du, Y. H. Su, and A. Sample, "2D+Depth RF Localization via a Low-Cost Receiver," *IEEE Wireless Communications and Networking Conference, WCNC*, pp. 1–6, 2024, doi: 10.1109/WCNC57260.2024.10571215.

[8] A. Kleniatis, A. Dimitriou, and A. Bletsas, "Device-Free Localization of Multiple Humans with Passive RFID and Joint RSSI-Phase Techniques," *2024 IEEE International Conference on RFID, RFID 2024*, pp. 35–40, 2024, doi: 10.1109/RFID62091.2024.10582592.

[9] V. Teeda, S. Moro, D. Scazzoli, L. Reggiani, and M. Magarini, "Differentiation and Localization of Ground RF Transmitters Through RSSI Measures from a UAV," *IEEE Trans Veh Technol*, vol. PP, pp. 1–10, 2024, doi: 10.1109/TVT.2024.3458416.

[10] L. Peled-Eitan and E. Greenberg, "Mobile User Localization Based on Wireless Sensor Network Signals in Smart Cities," *2024 IEEE International Conference on Microwaves, Communications, Antennas, Biomedical Engineering and Electronic Systems, COMCAS 2024*, pp. 1–4, 2024, doi: 10.1109/COMCAS58210.2024.10666174.

[11] W. Chen, T. Boroushaki, I. Perper, and F. Adib, "Reinforcement Learning for RFID Localization," *2024 IEEE International Conference on RFID, RFID 2024*, pp. 47–52, 2024, doi: 10.1109/RFID62091.2024.10582639.

[12] R. Fu, D. Xiao, and Y. Fan, "A novel cell phone localization solution for trapped victims based on compressed RSSI fluctuation range and PSO-BP neural network," *Meas. J. Int. Meas. Confed.*, vol. 225, no. September 2023, p. 114014, 2024,

doi: 10.1016/j.measurement.2023.114014.

[13] A. Ferrero-López, A. J. Gallego, and M. A. Lozano, "Bluetooth low energy indoor positioning: A fingerprinting neural network approach," *Internet Things (The Netherlands)*, vol. 31, no. March, p. 101565, 2025, doi: 10.1016/j.iot.2025.101565.

[14] A. G. Kakisim and Z. Turgut, "Multi-channel convolutional neural network with attention mechanism using dual-band WiFi signals for indoor positioning systems in smart buildings," *Internet Things (The Netherlands)*, vol. 29, no. May 2024, p. 101435, 2025, doi: 10.1016/j.iot.2024.101435.

[15] A. S. Lutakamale, H. C. Myburgh, and A. de Freitas, "RSSI-based fingerprint localization in LoRaWAN networks using CNNs with squeeze and excitation blocks," *Ad Hoc Networks*, vol. 159, no. March, p. 103486, 2024, doi: 10.1016/j.adhoc.2024.103486.

[16] R. R. Guerra, A. Vizziello, P. Savazzi, E. Goldoni, and P. Gamba, "Forecasting LoRaWAN RSSI using weather parameters: A comparative study of ARIMA, artificial intelligence and hybrid approaches," *Comput. Networks*, vol. 243, no. September 2023, p. 110258, 2024, doi: 10.1016/j.comnet.2024.110258.