Evaluating the Features of Indoor Positioning Systems Using Explainable AI

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***Abstract*—This paper investigates the application of Explainable AI (XAI) techniques in evaluating the features of indoor positioning systems, with a focus on improving model transparency and interpretability. Indoor positioning systems, crucial for location-based services in complex environments, rely heavily on machine learning models that often operate as black boxes. By performing SHAP (Shapley Additive explanations) and LIME (Local Interpretable Model-agnostic Explanations), this study aims to determine the most influential features by driving model predictions and provide a deeper understanding of their roles within the system. In this study, we investigate the features of RSSI values to check their importance and interactions, enhance the interpretability of the model through SHAP and LIME analyses, and guide future improvements in system accuracy and reliability.**

Keywords— explainable ai, wireless sensor network, indoor positioning, machine learning

I. Introduction

Indoor positioning systems (IPS) are potentially increasing for accurate location-based services within complex indoor environments such as multi-compartment buildings, shopping malls, and airports. Outdoor localization is heavily based on methods such as global positioning systems (GPS) and global navigation satellite systems (GNSS). However, with issues like irregular signal movements and complex environments [1], [2] those traditional methods cannot be used in indoor settings. Researchers introduce various indoor positioning techniques such as Wireless Sensor Networks (WSN), infrared (IR), Acoustic signals, Magnetic Field Mapping, and Vision-Based Localization to overcome these issues. WSN-based indoor positioning systems use various ranging techniques such as Received Signal Strength Indicator (RSSI) [3], Time of Arrival (ToA) [4], Time Difference of Arrival (TDoA) [5], Angle of Arrival (AoA) [6], Fingerprinting [3] and Hybrid Techniques [7] to determine the user's position or an object we are looking for.

This research uses WSN-based indoor positioning systems, leveraging signal strength indicators like the Wi-Fi Received Signal Strength Indicator (RSSI) to estimate the user's position. Because we can use existing infrastructures for WSN-based indoor positioning systems, it increases scalability, cost-effectiveness, low power consumption, and robust performance. For this research, we utilized the RSSI values of three Wi-Fi access points in the equilateral triangle on the ceiling to create a reliable reference network. We collected data in various time frames and situations, such as high population and non-population, with timestamps to increase the reliability and accuracy of data collection. We use the ESP 32 module to collect the RSSI values of fixed nodes and record them in an Excel file using Python script, which is the pre-processed data to remove the noise and extract meaningful information using Filtering techniques such as Moving Average, Fast Fourier Transform and Kalman Filter.

After preprocessing, the data was analyzed using various supervised models and neural networks, including Decision Tree, Random Forest (RF), Support Vector Regression (SVR), Linear Regression (LR), XGBoost (XGB), and Feedforward Neural Network (FNN). The performance of each model was evaluated using R^2 and Root Mean Squared Error (RMSE), with the Random Forest model on FFT data achieving the best results. This study aims to improve Indoor Positioning System (IPS) accuracy and interpretability by using Explainable AI (XAI) techniques, specifically SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations), to identify and evaluate the most influential features. These XAI techniques provide insights into the model's decision-making process, enhancing both the model's transparency and our understanding of the factors driving IPS predictions. This approach clarifies the current model's behavior. It is a roadmap for refining feature selection and preprocessing strategies, ultimately contributing to more accurate, interpretable, and robust IPS models for dynamic, real-world applications.

II. Related Works

The rapid expansion of technology could lead to a potential rise in the demand for Indoor positioning systems. It is used for asset tracking, navigating buildings, and other location-based services. In estimating positions, various localization algorithms have been proposed, broadly classified into two categories: they are divided into range-based and range-free two categories. Range-based techniques use some beacon nodes, such that when information is given from three or more beacon nodes, the range of an unknown node can be calculated. The node's position is then derived from this range of information. Some of the range-based algorithms are RSSI, AOA, TOA, and TDoA. On the other hand, range-free algorithms such as DV-Hop only depend on connectivity or proximity data of unknown nodes. The most used range-based method is the RSSI [8], considered the most accessible parameter for measuring the procedure. Still, it provides the most comprehensive interval of distance estimations, mainly if the environment is indoors, since the distance influences fading, shadowing, refraction, scattering, and reflections. As a result, several filters, such as the Extended Kalman Filter (EKF), FFT, and Moving Average Filter, have been used to reduce the variations in the RSSI signals [3].

FFT-based IPS uses the frequency domain representation of signals to derive features that can be used in positioning. These systems transverse time-domain signal to frequency-domain using FFT to detect diverse signal features related to

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location information. [9]. Above range-based and range-free techniques utilize various access technologies such as wireless sensor networks (WSN), infrared (IR), ultra-wideband (UWB), and radio-frequency identification tags (RFID) for precise indoor positioning [10]. The WSN can easily be scalable to any number of nodes and is cost-effective compared to other methods. Also, WSN can easily integrate with ML. Most positioning systems require the existence of one or more fixed nodes at known locations; the fixed nodes receive a signal from the mobile node, and the received signal is used to measure the parameter of the positioning [11].

Machine learning offers several advantages. Some machine learning algorithms can adapt when limited RSS data is available. The application of actual Wi-Fi eliminates the necessity of paying to add new tags, and the ability to work in non-line-of-sight (NLOS) conditions improves the accuracy of indoor usage. The approach described in the report, which is based on machine learning, leverages the available Wi-Fi in indoor environments that exist today. This prevents the requirement for further specific hardware or systems, which makes the method efficient and realistic for implementation in a realistic world [12]. RF is an ensemble learning approach that constructs many decision trees while utilizing the outcomes of each tree and avoiding overfitting. This reduces the chances of getting a wrong result since this method averages the results of several decision trees. This approach will help us to overcome the problem of the high probability of overfitting and will allow us to deal with significant amounts of data with higher dimensions. [13].

The need for adaptive IPS is crucial in dynamic Environments. Some literature proposed an adaptive learning framework to integrate positioning systems based on real-time environmental feedback [14]. In this approach, parameters were continuously updated based on changes in the signal conditions to maintain the system's accuracy. Another dimension implemented by reinforcement learning involves learning the best positioning strategies through the system's interaction with the given environment [15]. Various features can affect the output of indoor positioning systems. When implementing indoor positioning systems, explainable AI (XAI) technologies can analyze the importance of features and offer a transparent view of the predicted machine learning models. Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN) deep learning models combined to capture the signal patterns used in indoor positioning systems that Enhance the fingerprinting data with particle filters and autoencoders with the help of XAI techniques [16]. XAI is incorporated into the proposed system to provide an understanding of transparency and clarity on how the models we use make decisions [17].

This study's contributions include the Ability to identify the factors affecting the model's predictions by analyzing the inputs, which will serve to guide future efforts in optimizing feature selection, data collection strategies, and overall model performance in indoor positioning systems.

III. Methodology

This section describes the methodology used to evaluate the features of the proposed IPS through the application of SHAP and LIME. The process involves data collection, pre-processing, model training, and feature importance extraction using XAI techniques.

A. Data Collection and Preprocessing

In the current study, data was collected from three Wi-Fi access points in the ceiling in an equilateral triangle arrangement shown in Fig. 1. The dataset consists of RSSI values from three Wi-Fi access points configured as AP1, AP2, and AP3. The data was collected from the experimental setup where the mapped grid was one meter by one-meter square. All the data points are labeled in X and Y coordinates to experiment. The experimental area covered 193 m^{2}, as shown in Fig. 2. We collected data using an ESP32 module configured as a Wi-Fi scanner to acquire the RSSI values from Access points at each grip point in the mapped grid. ESP32 module was moved only to the X-axis and Y-axis to limit the study area to 2D space.

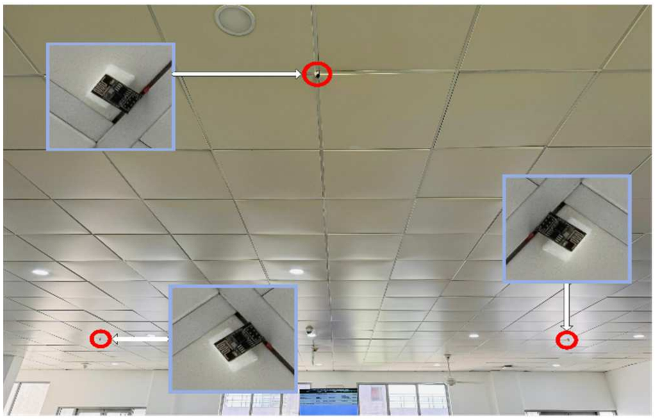

Fig. 1. Experimental Area with Three APs

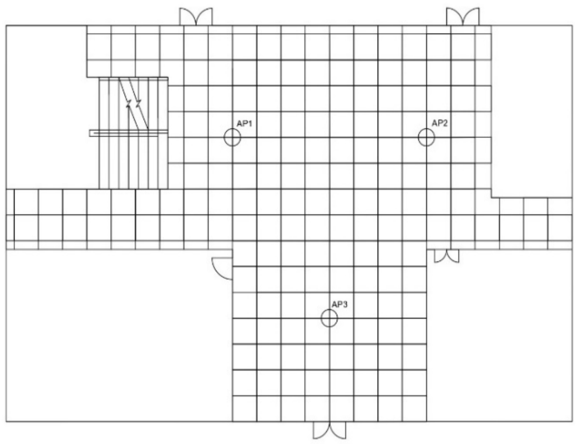

Fig. 2. Experimental Area Grid Map

Using a Python script, the data set was saved in an Excel file with columns named Timestamp, RSSI_AP1, RSSI_AP2, RSSI_AP3, X coordinate, and Y coordinate. To increase the accuracy and reliability of the data, readings are taken at a frequency of 1Hz at each data point, and measurements are taken in different situations, such as high population and non-population.

Data pre-processing is another crucial step in the study, as it removes the noise and extracts meaningful information from the data set. First, we clean the data set to remove the missing values and then ensure that RSSI values are within the valid range of -100dBm to 0dBm. Then, Fast Fourier Transform (FFT) filtering is used to enhance the quality of the RSSI signals. FFT was chosen due to its ability to reduce noise and extract relevant frequency components from the time-domain RSSI signals. The filtered data was normalized to ensure consistent scaling across features, facilitating better model training and analysis.

B. Model Training

The pre-processed data was used to train a machine learning model to predict the accurate position of the user. We used the Python 3.12.4 version to train the models with the help of libraries such as scikit-Learn, TensorFlow, pandas, NumPy, matplotlib, scipy, and filterpy. R^2 and RMSE are used to evaluate the performance of models. R^2 value measures the proportion of the variance in the dependent variable that is predictable from the independent variables. If the R^2 value is closer to 1, the model shows a high proportion of the variance. RMSE measures the average magnitude of the prediction errors, providing insight into the model's accuracy by indicating how far the predicted position deviates from the actual position. A lower RMSE indicates better model performance.

The model was trained to predict the X and Y coordinates based on the FFT-filtered RSSI values. This process involved splitting the dataset into 70% for training and 30% for testing, ensuring that the model was evaluated on unseen data to assess its generalization capabilities.

C. Application of Explainable AI Technique.

Explainable AI encompasses strategies and processes intended to clarify and explain the decision-making process of AI models to humans. In the machine learning domain, where models are sometimes treated as 'black boxes,' XAI contributes insights into the reasoning behind a model's decisions rather than merely presenting a result. This is critical for applications such as indoor positioning, wherein the accuracy and clarity of decisions are fundamental for reliability, safety, and user trust. We employed two Explainable AI techniques to analyze the importance of features and offer a transparent view of the predicted machine learning model: Shapley Additive explanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME).

1) SHAP Analysis

A robust cooperative game theory-based technique called SHAP analysis clarifies the output of any machine learning model by assigning importance levels (SHAP values) to all features. Within indoor positioning systems (IPS), SHAP is used to analyze how each input feature, particularly the filtered RSSI values from access points labeled AP1, AP2, and AP3, relates to the prediction of an object or user location. SHAP measures the global importance of features in all predictions and local explanations or individual predictions. A SHAP summary plot was used to capture the overall effect of each feature on the model. Furthermore, SHAP dependence plots were employed to visualize the interactions between individual features and the corresponding SHAP values.

2) LIME Analysis

LIME was used to produce localized explanations of specific predictions. Being model agnostic, LIME can be applied to any machine learning model. In this research, LIME locally approximates the behavior of the Random Forest model for a selected instance by fitting a simple and interpretable model, such as linear regression, on the input data that has been slightly modified around the selected instance. The use of LIME analysis enabled the understanding of how alterations to RSSI values impacted the predicted coordinates for cases and offered a more explicit model decision-making perspective.

IV. Results and Discussion

This section presents the SHAP and LIME results, providing insights into the importance of the feature and its impact on indoor positioning system predictions due to environmental factors. The results from both methods have been conducted and compared to validate the consistency and reliability of the findings, thus enabling actionable insights for improvement in the feature selection and preprocessing techniques in future iterations of the IPS.

A. SHAP Analysis

The SHAP analysis estimated the global and local importance of the RSSI features (RSSI1_fft, RSSI2_fft, RSSI3_fft). The SHAP summary plots provide a comprehensive view of the contribution of each of the features toward the model prediction for a particular instance, positively or negatively. Positive sharp values show how the feature increases the predicted X or Y coordinate, and negative SHAP values show how the feature decreases the prediction. The magnitude of the feature values is represented using the color gradient. Blue indicates the weak RSSI values, and red means the Strong RSSI values.

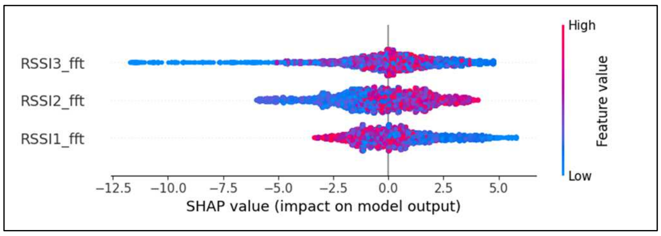

Fig. 3. SHAP Value for X Coordinates

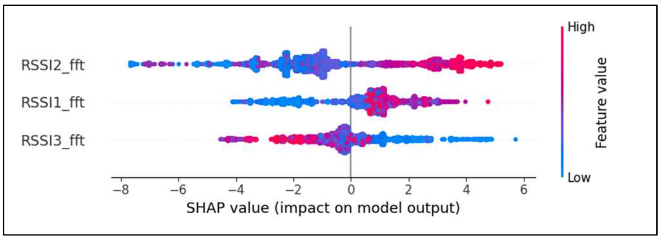

Fig. 4. SHAP Values for Y Coordinates

Fig. 3 shows the impact on the model's prediction for X coordinates. The most influential negative feature was RSSI3_fft since it has a much spread of the negative side of SHAP values. It means that this feature often decreases the predicted X coordinate. Also, it shows the more extensive spread of the SHAP values, indicating a strong influence for X coordinates pulling down the value. The value of RSSI2_fft is clustered around zero, showing that features don't heavily influence the model's prediction. RSSI1_fft showed a high influence on low feature values and a low influence on higher feature values. Therefore, changes in RSSI1_fft show more variability in how they influence the model predictions, and it shows the opposite effect on the X coordinate predictions.

Fig. 4 shows the impact on the model's prediction for the Y coordinate. In this plot, RSSI2_fft shows the wide range of SHAP values, and it has a solid negative influential feature for the model's prediction of Y coordinates. RSSI1_fft shows the more prominent spread of the SHAP values, with low feature values negatively impacting Y coordinate predictions and higher values having a positive impact. In this plot, RSSI3_fft has the least impact compared to other values, which generally contributes negatively to the prediction.

B. LIME Analysis

LIME was used to provide a local explanation for any instance, describing how the model reaches any prediction. Fig. 5 and Fig. 6 show the LIME explanation for one such instance. The LIME explanation for the X prediction plot shows how RSSI values change the predicted X coordinates. In Fig. 5, RSSI2_fft has the most positive contribution to the prediction of X coordinates, and it increases the prediction. RSSI1_fft has a negative impact on the prediction. RSSI3_fft also positively impacts prediction but is not as good as RSSI2_fft. The LIME explanation for the Y prediction shows how the RSSI values lead to changes in the Predicted Y coordinates.it is shown in Fig. 6. As shown in the figure, RSSI1_fft has the most positive impact on the prediction, and the RSSI2_ftt and RSSI3_fft have a negative effect on the prediction, and they reduce the prediction.

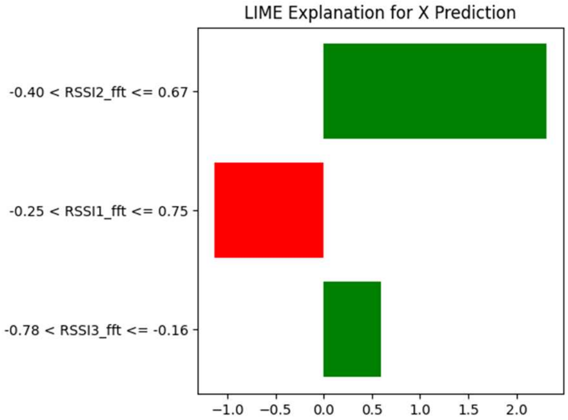

Fig. 5. LIME Explanation for X Coordinates

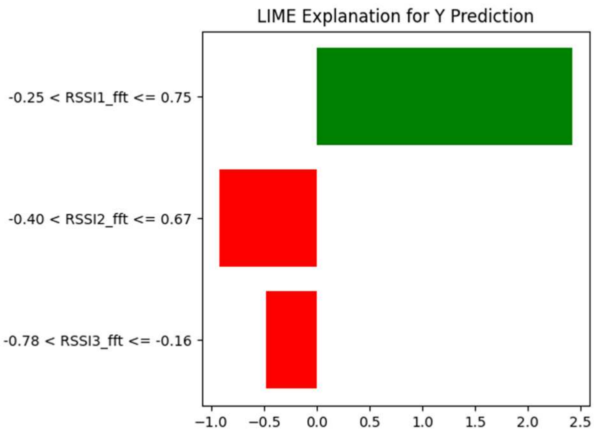

Fig. 6. LIME Explanation for Y Coordinates

C. Comparative Analysis of SHAP and LIME Results

RSSI1_fft and RSSI2_fft show the strongest contribution to both X and Y predictions in the LIME plot. When comparing both techniques, RSSI3_fft influences the X coordinate more, and RSSI2_fft influences the Y coordinate more. When discussing the impact of access point imbalance on data collection setup in Fig. 2, three APs are fixed in the equilateral triangle on the ceiling. A slight imbalance can be due to environmental factors such as obstacles and free space. For example, obstacles near AP1 and AP2 or more open space near AP3 cause RSSI3_fft to have more data and, hence, a stronger influence on the model, particularly for the X coordinates prediction. As seen in the SHAP values for the Y coordinate, RSSI3_fft has a strong negative influence due to this imbalance. Also, RSSI2_fft's neutral effect on X coordinate prediction might be because less is collected from AP2, weakening its influence on prediction. In contrast, RSSI2_fft strongly impacts the Y coordinate, potentially indicating that AP2 plays a more significant role in determining positions along the Y-axis, where environmental imbalance less affects data coverage. The consistency between SHAP and LIME results aligns the predictions and validity of the feature importance findings.

V. Conclusion

This study applied Explainable AI techniques, specifically SHAP and LIME, to evaluate the importance of features in a wireless sensor network-based indoor positioning system. Predictions of the X and Y coordinates of the user's position were obtained from a Random Forest model trained on FFT-filtered RSSI values. SHAP analysis provided global interpretability by highlighting the importance of each RSSI value. LIME offered a local explanation, reinforcing the importance of RSSI2_fft for X predictions and RSSI1_fft for Y predictions. The coherence between the SHAP and LIME results validates the reliability of the same results, allowing a greater level of transparency in the model's decision-making process. These insights guide further feature selection and preprocessing improvements to make indoor positioning systems more accurate.

Considering these insights, future work could focus on retraining the model using the most impactful features identified by XAI analysis. This targeted approach has the potential to streamline the model, improve interpretability, and possibly boost prediction accuracy by reducing noise from less informative features. Additionally, data rebalancing strategies should be considered to address the imbalance in data collection from the access points. This may be done by altering the access point configuration or obtaining further data from sections of the map that were not sampled.

Furthermore, derivative feature engineering or suitable regularization techniques could be explored to ensure that the model does not overly rely on any single feature, promoting a balanced prediction outcome. The insights from SHAP also underscore the need to improve model explainability, particularly in environments prone to signal interference or physical obstructions. By addressing these considerations, future iterations of indoor positioning systems could achieve greater accuracy, robustness, and practical applicability in complex indoor environments.

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