XAI empowered dual band Wi-Fi based indoor localization via ensemble learning

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XAI Empowered Dual Band Wi-Fi Based Indoor Localization via Ensemble Learning

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***Abstract*—Wi-Fi technology is widely used in indoor positioning systems due to its ubiquitous presence in almost every building and its cost-effectiveness without requiring additional hardware. To mitigate the effects experienced by wireless networks, dual-band Wi-Fi studies have gained importance. In this study, the UTMInDualSymFi dataset is utilized to evaluate the performance of single-band and dual-band Wi-Fi localization using 2.4 GHz and 5 GHz Wi-Fi data. For localization, KNN (K-Nearest Neighbor), XGBoost, Decision Tree, and Random Forest techniques are used for classification, and a multi-view ensemble learning approach is proposed for increasing accuracy. The results are evaluated using explainable neural network models: SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations), and the effectiveness of single-band versus dual-band localization is assessed, along with the contribution of each access point to localization accuracy.**

Keywords—indoor localization, Wi-Fi, dual band, explainable neural network, multi-view ensemble learning.

I. INTRODUCTION

Indoor positioning systems recommended for locating the position of objects or people inside buildings, especially smart cities, smart buildings, and smart homes, which have attracted great interest recently, are becoming an indispensable technology. Indoor positioning systems are used in many different areas, including hospitals and other healthcare environments to track the location of patients, airports to show passengers where they are currently and plot the fastest route to their destination, and factories to track the location of manufactured products. However, indoor localization is particularly challenging, unlike the estimation process of various outdoor locations [1], since the GPS technology used for outdoor location estimation does not work effectively in indoor areas. Therefore, different technologies such as Wi-Fi, RFID, Bluetooth, Bluetooth Low Energy, and IrDA are used to provide indoor positioning solution [2]. However, it is especially important to offer approaches based on technologies that can be found in every building in order to find a realistic, feasible, universal solution and reduce the hardware cost. Especially since Wi-Fi access points are found in almost every building, Wi-Fi technology is frequently used for indoor location determination. However, because indoor spaces have high and variable dynamics, Wi-Fi signals may fluctuate over time due to different conditions. For example, the number of objects and people indoors may vary, and this may cause distortion and scattering in the signal values used for location detection. Also, different influences, such as internal noise of signal collecting devices, can adversely affect position detection. In order to deal with these effects and to increase the accuracy of indoor location estimation, methods with many different preprocessing steps such as filtering, normalization, and dimension reduction are presented in the literature [3].

Indoor positioning generally uses deterministic methods such as trilateration based on the use of signal timestamps from the three devices and triangulation based on the use of the arrival angles of the signal values, and fingerprinting approaches based on creating signatures by navigating the space and recording the signals step by step. Fingerprinting approaches create indoor grids (called as reference points) for a building or floor, and generally transforms the indoor localization problem to a classification or regression problem. Therefore, many different learning architectures such as machine learning and deep learning are presented for indoor localization [4]. Recently, in order to improve indoor positioning performance, studies have been presented based on using different frequencies obtained from access points with dual-band property that enable a device to operate in two different frequency bands. Wi-Fi 2.4G signals are more transparent and less susceptible to obstacles, while Wi-Fi 5G signals are more stable and have lower jitter [5].

In the existing literature, numerous studies have been conducted on indoor localization utilizing dual band WiFi technology, 2.4GHz and 5GHz as follows.

Yang et al. [6] introduced a new approach called "Fingerprinting Pyramid Maps" (FPM) that offers users the flexibility to choose a combination of localization area and time preference. AP Pairing Algorithm (AP_PA), takes advantage of the crossover frequency RSS difference (RSSD_CF) between each pair of AP sensors, effectively mitigating the limitations imposed by device heterogeneity. Zhao et al. [7] introduced an algorithm that effectively captures a robust positioning feature from Wi-Fi signals, employing kernel principal component analysis (KPCA). To improve localization accuracy and alleviate computational complexity, they incorporate a Wi-Fi signal choosing algorithm and a coarse localization scheme. The estimated location is then obtained using the weighted k-nearest neighbor method (WKNN). Junhua Yang [8] presented a novel localization system called the dual-frequency difference and cubic spline interpolation (DFD-CSI) in their work. A fingerprinting database includes data from both frequency bands as well as the difference between them. Additionally, cubic spline interpolation is employed to refine the coarse fingerprint database, thereby reducing the time required for site exploration while maintaining localization accuracy. Own et al. [5] conducted a study where they utilized an SVM (Support Vector Machine) model to differentiate between Non-Line-of-Sight (NLoS) and Line-of-Sight (LoS) environments. In addition, they employed a capsule network to estimate user position. Authors conducted a comparative analysis with traditional indoor positioning methods and performed robustness tests using simulation data. Karlsson et al. [9] employed particle filter along with the known signal strengths from Wi-Fi access points to facilitate indoor navigation. By utilizing dual band frequencies, they obtained more comprehensive information, leading to enhanced accuracy in positioning. Tahat et al. [10] conducted a study to increase the accuracy and robustness of Wi-Fi fingerprinting-based Indoor Positioning Systems (IPS) by using machine learning classification algorithms. The numerical results demonstrate that the proposed IPS effectively predicts device location by employing a subset of the considered ML classification algorithms. Incorporating dual-frequency information in the location process enhances its efficiency and robustness. Zhang et al. [11] carried out a study using empirical simultaneous measurements to examine the performance of different machine learning (ML) classification algorithms for defining the location of Wi-Fi receiving devices in both single-band and dual-band operation. The integration of dual-frequency information in the IPS improved the efficiency and robustness of the location process. Lee et al. [12] developed a hybrid localization algorithm to enhance the accuracy of distance measurement in indoor non-line-of-sight (NLOS) conditions. To achieve this, they replaced the ranging component of a rule-based localization technique with a deep regression model that leverages data-driven learning based on dual-band received signal strength (RSS).

This study presents an investigation on indoor positioning utilizing dual band Wi-Fi technology. The UTMInDualSymFi dataset [13], which incorporates Wi-Fi data from both the dual band and the 2.4GHz and 5GHz single bands, was created using the fingerprinting technique and employed for this purpose. Various machine learning techniques including KNN (K-Nearest Neighbor), Decision Trees, Random Forest, and XGBoost were utilized to determine the location. It was observed that the Random Forest classifier provided the highest accuracy when utilizing the dual band data. To further enhance the accuracy, we propose an indoor localization system that applies Random Forest in parallel on three different feature areas, which we consider as views coming from different angles, and estimates the location by averaging over the results. Signal features obtained from 2.4 GHz frequency band, 5 GHz frequency band and dual band were evaluated as separate views. To interpret and explain the predictions of the proposed system, two different explainable artificial intelligence models (XAI) approaches: SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations). LIME model is used to explain each individual indoor prediction. It generates local information about the distribution of the localization prediction probabilities of the proposed system. The SHAP model provides global interpretations about the Wi-Fi access points, which is discriminative that the proposed system mainly uses in determining reference points. The XAI models are integrated into the proposed learning phase so that the system's prediction results can be validated and analyzed. Since the indoor localization problem has a high and variable dynamics, in case the proposed system produces unexpected results, analysis of possible variable states of the environment, object, and signal generating devices can also be provided. The experimental results demonstrate that the proposed model increases the indoor localization performance for UTMInDualSymFi dataset.

II. METHODOLOGY

This study employs a fingerprinting based approach for indoor localization. UTMInDualSymFi dataset [13], which was generated using the fingerprinting technique, is utilized for this purpose. The positioning is performed using the 2.4GHz Wi-Fi, 5GHz Wi-Fi, and dual band Wi-Fi data included in the related dataset. To achieve this, machine learning techniques including KNN, Decision Tree, XGBoost, and Random Forest are employed. Furthermore, a multi-view ensemble learning model is proposed to enhance the results obtained from the dual band dataset. The outcomes of the proposed approach are analyzed and interpreted using explainable artificial intelligence models, SHAP and LIME.

A. *Fingerprinting*

The fingerprint method, an analysis technique commonly employed for indoor positioning, was utilized to perform indoor location determination. This technique comprises two distinct stages: offline and online [4].

In the offline phase, the fingerprint method involves mapping the signal characteristics of the target area where location detection is desired. In the online phase, the signals received from the user are compared to the signal information stored in the previously created signal map, enabling precise positioning. Various devices capable of signal scanning, such as mobile phones, tablets, wearable technologies, and laptops, can be utilized to collect the relevant signals in both phases. The signal values used for fingerprint map creation typically include received signal strength indicators, which serve as differentiators in the environment. Fig. 1 represents the phases of the fingerprinting method.

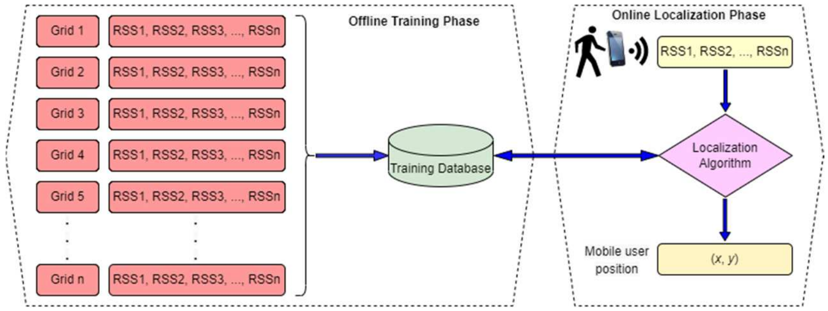

Fig.1. Fingerprinting method

- Offline phase: This phase involves extracting the signal map of the target positioning area. During this phase, the zones where the mobile user may be located are divided into grid-based reference point areas. The width of each grid's reference point area directly affects the accuracy of positioning. In creating the signal map, a sampling approach is employed to gather signal samples from the grids. These samples can be obtained either from the midpoints of the grids or by walking along random routes within the grids, collecting samples from both the edges and midpoints. It is crucial to select various time periods and scenarios that exhibit different characteristics of the indoor space during the collection of signal samples. This ensures the creation of a signal sample set that reflects all possible situations within the targeted indoor environment. Similarly, using multiple devices during the signal sample collection process is important to capture the measurement variations that may arise due to device differences in the signal maps.
- Online phase: In this stage, the signal values received from the mobile user are compared with the values stored in the signal map created during the offline phase. Various techniques, such as statistical methods, machine learning, and deep learning, can be employed for these comparisons. The goal is to find a match between the signal information obtained from the mobile user's current location and the signal map stored in the database that represents the known locations. This comparison process helps determine the class or location that best corresponds to the received signal information, enabling accurate indoor positioning.

B. *Dataset*

In this work, the authors utilized the UTMInDualSymFi dataset [13], which contains dual band 2.4 GHz and 5 GHz Wi-Fi signal information, to propose a dual band Wi-Fi-based approach [9]. The dataset consists of data collected from four different buildings. The authors focused on location determination based on floor and building wing in their work. Our study aims to achieve higher positioning precision by considering reference points assigned at 1-meter intervals in the F04 and CX1 buildings within the dataset. This approach enables more accurate positioning.

The F04 building dataset includes raw Wi-Fi dual band data from 64 access points, covering 2 floors and 3 wings on each floor. A total of 120 reference points were assigned, with 20 on each relevant wing. The CX1 building dataset includes raw data from 71 access points and 130 reference points. The CX1 building comprises 2 floors and 2 wings, with a total of 130 reference point assignments. Training and test data for both buildings were collected at different times using two different devices.

To ensure a hardware-independent approach, two different devices were used to collect Wi-Fi signal values in the datasets. In this study, the data collected from both devices were combined and utilized together.

C. *Indoor Localization*

In this research, KNN, Decision Trees, XGBoost, and Random Forest techniques are utilized to match the signals present in the fingerprint map, enabling indoor positioning. Moreover, a multi-view ensemble learning approach is introduced in the study.

- K-Nearest Neighbor: The K-nearest neighbor classifier (KNN) is a machine learning methodology grounded in the principles of Bayes' theorem [14]. This classification process entails considering the k value that is in closest proximity and employing the majority rule for decision-making [14].
- Decision Tree: Nodes within decision trees possess the capability to evaluate a dataset based on any attribute [15]. Depending on the attribute value received, nodes branch out into two or more sub-trees. The process of constructing and splitting a decision tree is determined by calculating impurity measures [15]. When all values directed to a particular node exhibit identical characteristics, that node is deemed pure and assigned an impurity value of 0. In situations where the impurity value is 0, there is no necessity to partition the node further into sub-nodes.
- XGBoost: The machine learning technique that utilizes tree-based models. The construction of each tree is guided by the maximum depth value. In cases where excessive downward growth is observed during tree formation, pruning techniques are employed to mitigate the risk of overfitting [16]. While the Gradient Boosting algorithm employs a first-order function to compute the loss function, XGBoost

employs second-order functions for this purpose. Additionally, XGBoost's parallel operation capability enhances its efficiency, enabling faster results compared to similar algorithms [16].

- Random Forest: Random forests are a type of ensemble model that combines multiple individual tree predictors [17]. In a random forest, each tree's construction is influenced by a randomly chosen vector, sampled independently from the same distribution across all trees. With an increasing number of trees in the forest, there is a high probability that the forest's generalization error will approach a certain limit. The generalization error of a random forest is determined by two factors: the individual strength of each tree in the forest and the level of correlation among the predictions made by different trees [17]. Stronger and less correlated trees tend to result in lower generalization errors for the forest.
- Multi-View Ensemble Learning: In this article, first, we aimed to analyze how the accuracy performance in indoor location prediction changes according to different Wi-Fi data such as 2.5G, 5G and Dual-band Wi-Fi. After this analysis, to increase the accuracy performance, we propose a multi-view based indoor position prediction model. We chose the Random Forest algorithm that is an ensemble learning algorithm due to its advantages such as easy implementation, simplicity, and effectiveness. The random forest algorithm creates multiple single trees based on random samples of the training data. We use averaging strategy to obtain final prediction probabilities from the prediction results belonging to the decision trees. Multi-view classification focuses on increasing classification accuracy by revealing distinctive patterns from different angles on the data obtained from different views. Generally, mapping the resulting multiple views into a single space, that is, combining spaces, is the first approach. The obvious disadvantage of this situation is that the vector or matrix size increases due to the direct combining of the feature spaces. On the other hand, in a feature space where multiple views are learned together, learning can be adversely affected if information about a view cannot be obtained. We use each Wi-Fi data as a separate view. In this case, each of the 2.54GHz, 5GHzand dual-band data is defined as a view. Using an ensemble model, we perform a separate learning for each view. For each view, we obtain a final probability of assignment by averaging the results from the trained models, that is, the probabilities of assigning a sample to reference points. The reference point with the highest probability for a newly arrived sample is estimated as the location of the sample. The proposed multi-view ensemble learning framework is given in Fig. 2.

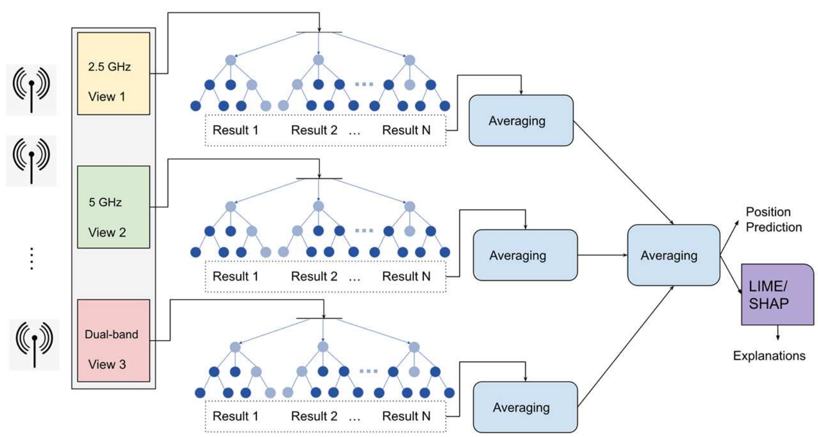

Fig.2. Multi-view ensemble learning

D. Explainable Artificial Intelligence Models

Explainable Artificial Intelligence (XAI) models have been developed to provide transparency and interpretability to learning models by revealing their decision-making processes [44]. Understanding the decision stages of artificial intelligence models has become challenging for both users and experts. Likewise, in the domain of indoor localization, it is essential to comprehend and interpret the impact of specific access points on the accurate or inaccurate prediction of locations, as well as the extent to which the Wi-Fi signal values received from these access points contribute to the prediction outcome.

- LIME (Local Interpretable Model-Agnostic Explanations): LIME operates on a local level, meaning that its explanations are specific to individual observations [18]. LIME provides explanations for predictions based on each specific observation. LIME accomplishes this by constructing a local model utilizing sample data points that closely resemble the observation under scrutiny. For each observation

x, the explanations generated by LIME are obtained through equation (1) [18].

$$\Phi(x) = \arg\min_{g\in G} L(f, g, \pi_x) + \Omega(g) \quad (1)$$

Here, G represents the set of potentially interpretable models, for instance, linear models and decision trees, $g \in G$: The concept of an explanation is regarded as a distinct model, $f: \mathbb{R}^d \to \mathbb{R}$ and $\pi_x(z)$ indicates the proximity measure of an instance z from x, $\Omega(g)$: A metric to quantify the complexity of the explanation, $g \in G$.

The objective is the minimization of the locality aware loss L without taking any assumptions into consideration related to the underlying function f, as LIME is designed to be model agnostic. L represents the measure of the discrepancy between the approximation g and the actual function f within the locality stated by $\pi(x)$.

- SHAP (SHapley Additive exPlanations): In the SHAP framework, the predictions' uncertainty is distributed among the covariates, facilitating an evaluation of the contribution of each explanatory variable to individual predictions [18]. This evaluation is conducted without dependence on the underlying model. SHAP, which stands for SHapley Additive exPlanation, employs Shapley values to represent model predictions as linear combinations of binary variables. These binary variables indicate whether each covariate is included or excluded in the model. By employing this approach, the influence of each explanatory variable on the model's predictions can be quantified.

The SHAP algorithm represents model predictions as linear combinations of binary variables, indicating the presence or absence of each covariate in the model. More formally, it approximates each prediction $f(x)$ with $g(x')$, which is a linear function of the binary variables $z' \in \{0,1\}^M$ and the quantities $\emptyset_i \in \mathbb{R}$,. These quantities are stated as in the equation (2) [18].

$$g(z') = \phi_0 + \sum_{i=1}^{M} \phi_i z'_i \quad (2)$$

Here, in the model, the number of explanatory variables is represented with M. Only additive method that fulfills the properties of local accuracy, missingness, and consistency is achieved by assigning to each variable x'_i an effect ϕ_i (the Shapley value), which is given in equation (3) [19].

$$\phi_i(f, x) = \sum_{z' \subseteq x'} \frac{|z'|!\,(M - |z'| - 1)!}{M!} f_x(z') - f_x(z' \setminus i) \quad (3)$$

In equation (3), f represents the model, x and x' represent the available variables and the selected variables, respectively. The term $f_x(z') - f_x(z' \setminus i)$ quantifies, for each individual prediction, the deviation of Shapley values from their mean, representing the contribution of the i-th variable.

III. RESULTS AND DISCUSSION

A. Classification Results

Table 1 presents the classification results performed using different Wi-Fi bands in the F04 and CX1 buildings. In the F04 building, the highest accuracy achieved using the 2.4GHz Wi-Fi band is 85.86% with the Random Forest classifier. Similarly, in the CX1 building, the Random Forest classifier achieves the highest accuracy of 87.71% using the 2.4GHz Wi-Fi band. Although the accuracy decreases when using the 5GHz band in both buildings, the Random Forest classifier still exhibits the highest accuracy. The accuracy rates obtained are 83.23% in the F04 building and 87.71% in the CX1 building.

When considering the results obtained using the dual bands, it is observed that the accuracy rates increase, surpassing the accuracy achieved when using the individual 2.4GHz and 5GHz bands. In the F04 building, the accuracy rate reaches 91.21% with the Random Forest classifier, and in the CX1 building, it reaches 89.37%. These results indicate that the combined use of the 2.4GHz and 5GHz bands yields more accurate positioning.

TABLE 1 CLASSIFICATION RESULTS

Building	***Data***	***KNN***	***DT***	***XGBoost***	***RF***
F04	*2.4GHz*	0.5182	0.7020	0.7859	0.8586
	5GHz	0.6919	0.7051	0.7869	0.8323
	Dual	0.6556	0.7333	0.8162	**0.9121**
CX1	*2.4GHz*	0.4700	0.6404	0.7907	0.8771
	5GHz	0.6512	0.6913	0.7439	0.8188
	Dual	0.5832	0.7221	0.7822	**0.8937**

Table 2 presents the results obtained using the proposed multi-view ensemble learning approach in the F04 and CX1 buildings. In the F04 building, the highest accuracy rate achieved was 91.21%. However, by applying the proposed multi-view ensemble learning approach, the accuracy rate further improved to 92.53%. Similarly, in the CX1 building, the initial accuracy of 89.37% increased to 91.48% when using the proposed method. The proposed approach handles the 2.4GHz and 5GHz Wi-Fi signals separately and evaluates them using distinct learning models. This strategy leads to more robust results in indoor location detection, as evidenced by the higher accuracy rates obtained. By utilizing a multi-view ensemble learning approach, the method effectively leverages the strengths of both bands, resulting in improved accuracy and enhanced robustness in the positioning process.

TABLE 2 RESULTS OF PROPOSED METHOD

		RF			**Proposed Method**		
Building	***Data***	***Accuracy***	***Precision***	***Recall***	***Accuracy***	***Precision***	***Recall***
	2.5G	0.8586	0.8738	0.8763			
	5G	0.8323	0.8680	0.8476	**0.9253**	**0.9301**	**0.9387**
F04	Dual	0.9121	0.9293	0.9263			
	2.5G	0.8771	0.8936	0.8867			
	5G	0.8188	0.8622	0.8325	**0.9148**	**0.9308**	**0.9233**
CX1	Dual	0.8937	0.9173	0.9024			

B. XAI Results

The results obtained with Random Forest model were analyzed using LIME model for three different views (2.4 GHz, 5 GHz, dual-band) . A sample was selected to analyze LIME's explanation of indoor localization estimates. The prediction probabilities of the reference points calculated by the learning algorithm for the selected sample are presented by LIME. Access points that are effective in allocating the sample selected as a test to the current reference point and the attribute distribution of these points are produced by LIME.

Fig. 3 shows the estimation results obtained by the learning model using the LIME model of the selected test sample, according to the 2.4GHz Wi-Fi values. The property values represent the signal strengths received from the corresponding access point. The selected test sample is correctly assigned to reference point (Grid) 119 by the learning algorithm. It is observed that the attributes that are more responsible for assigning the test sample to reference point 119, in other words the distinctive access points, are access points 24, 28, 7, 29, 11, 34 and 27. For this example, it is observed that the signal strength of access points 24, 7, 11, 27 is taken as 100. It is concluded, based on this example, that signals from these access points are generally not received on Grid 119. It is seen that the signal strength of access point 28 is taken as -100. In this case, it is concluded that access point 28 is located quite close to Grid 119. It is seen that -62 and -59 signal values are obtained from access points 29 and 34, respectively. These access points may be more distant from Grid 119 than access point 28, or there may have been a decrease in signal strength due to exposure to an external factor. It is seen in Fig. 3 that the selected test sample is assigned to Grid 119 with a probability of 44 percent and to Grid 118 with a probability of 29 percent. It is noteworthy that grid 118, which is the neighboring grid, possesses the second highest probability. The LIME model shows that access points 13 and 6 for the selected test sample have signal values compatible with the feature distribution of Grid 118.

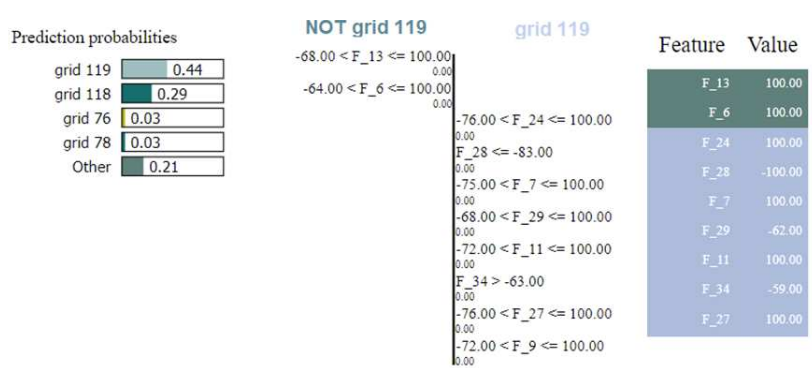

Fig.3. LIME results for 2.4GHz Wi-Fi based localization

Fig. 4 shows the explainable results obtained with the LIME model for the same selected test data, using a 5 GHz Wi-Fi dataset. Similarly, this test sample is correctly allocated to Grid 119. Fig. 4 gives the attribute values of the nine most important access points identified by the model as distinctive attributes in allocating the test sample to Grid 119. In Grid 119 location, it is seen that signals are received from APs 58, 64, and 63 in the 5GHz band range. When using 5GHz frequency values directly, it is seen that the prediction probability belonging to Grid 119 that the learning model calculates is higher than the probability value when using 2.4GHz frequency values. Grid 118, representing the neighboring grid has the second highest probability and similarly, the prediction probability belonging to Grid 118 is calculated higher than the probability given in Fig. 3. Unlike 2.4 GHz frequency values, when using 5GHz frequency values, it has been observed that the prediction probability values of the model belonging to other reference points are lower for this sample.

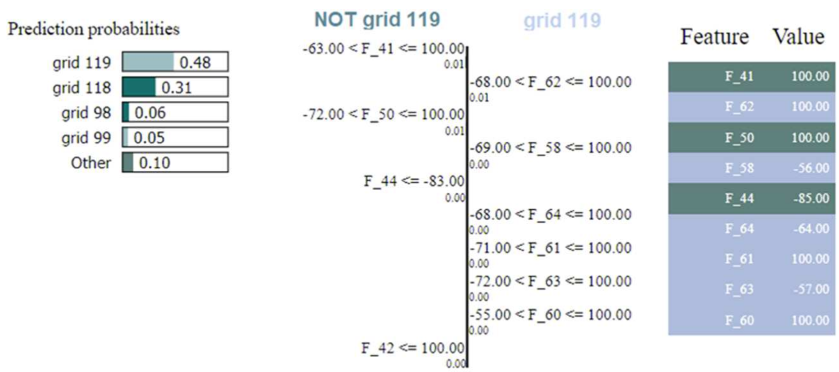

Fig.4. LIME results for 5GHz Wi-Fi based localization

The results of the LIME model analysis for the test sample when learning and testing with dual-band Wi-Fi signals are presented in Fig. 5. According to the results, the probability of being within grid 119 for the test sample has decreased compared to the results of single-band analysis. In the classification performed using 2.4GHz, the probability value was 0.44, while in the classification using 5GHz, it was 0.48. However, when dual-band Wi-Fi data was used, the probability value decreased to 0.37. Access points 28, which are effective in the 2.4 GHz scenario, and AP 64 and 58, which are effective in the 6 and 5 GHz scenarios, are effective together in allocating this sample to Grid 119.

To summarize the results obtained from the LIME model, using two different bands together in the same feature space may reduce the prediction probabilities for some samples. Although using two different bands together in the same feature space enriches the feature space, combining different frequencies can increase the probabilistic complexity of the learning model due to the influence of different factors. Therefore, in this study, it was aimed to achieve a higher performance in indoor location estimation by performing different learning phase for each different band space and then averaging the prediction results.

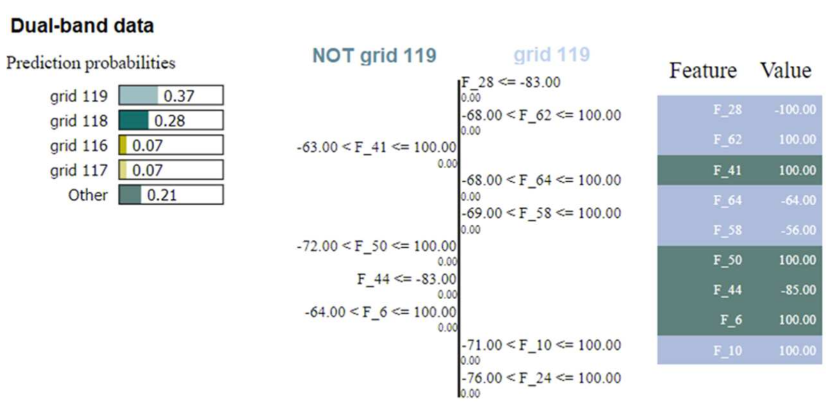

Fig.5. LIME results for dual band Wi-Fi based localization

Fig. 6 presents the SHAP global analysis results of the proposed method. The global analysis results provide a detailed analysis of which features are more effective for which classes during the learning and testing process of the model, considering all train samples and test samples. It demonstrates the average impact of top eight access points (features) on model prediction for reference points between 0 and 9. Top features such as 48, 43, 61, or 40 are the most highly ranked access points.

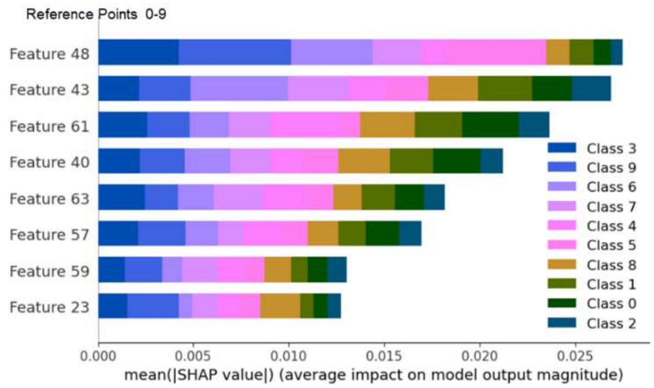

Fig.6. SHAP results for reference points between 0 and 9.

Similarly, Fig. 7 gives the average impact of top eight access on model output for reference points between 110 and 119. For these reference points, APs 47, 58, 61, or 43 are highly important for indoor localization prediction.

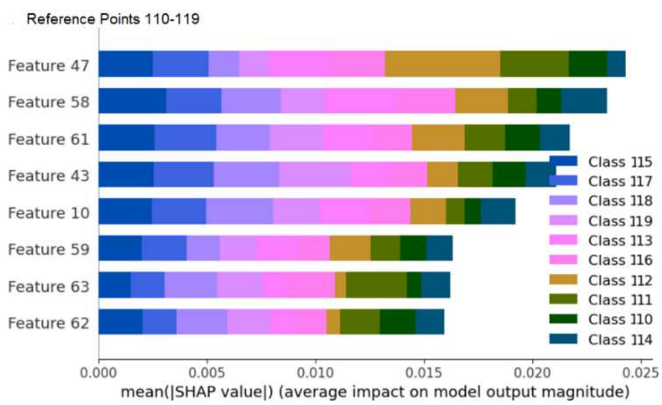

Fig.7. SHAP results for reference points between 110 and 119.

IV. CONCLUSION

This study focuses on the utilization of Wi-Fi technology in the development of indoor localization systems. Specifically, it presents an indoor location detection approach using the UTMInDualSymFi dataset, which includes datasets for 2.4GHz Wi-Fi, 5GHz Wi-Fi, and dual-band Wi-Fi (both bands combined). The study employs fingerprinting-based indoor positioning techniques utilizing single-band and dual-band data with classifiers such as KNN, Decision Tree, XGBoost, and Random Forest. The Random Forest classifier achieved the highest accuracy, reaching 91.21% for the F04 building and 89.37% for the CX1 building when using dual-band data. To address the potential impact of different bands on positioning accuracy, a multi-view ensemble learning approach is proposed. With this approach, the accuracy improved to 92.53% in the F04 building and 92.33% in the CX1 building. The obtained results are further analyzed using LIME and SHAP XAI models. Specifically, the LIME model examines the signal values for the sample 119 grid, revealing higher probability values for grid 119 in single-band classifications, which decrease in dual-band Wi-Fi classification. This highlights the consistency of the multi-view ensemble learning model, which combines individual band classifications. Additionally, the study discusses the effects of the SHAP model on identifying grid areas of access points. For future studies, the aim is to develop a classification approach that takes into account access points that are distinctive for each grid, utilizing XAI methods.

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