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RADIO FREQUENCY BASED INPAINTING FOR INDOOR LOCALIZATION USING MEMORYLESS TECHNIQUES AND WIRELESS TECHNOLOGY

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Abstract. *Recently, the Internet of Things (IoT) has grown to encompass the surveillance of devices through the utilization of Indoor Positioning Systems (IPS) and Location Based Services (LBS). One commonly used method for developing an Intrusion Prevention System (IPS) is to utilize wireless networks to determine the location of the target. This is achieved by leveraging devices with known positions. Location-based services (LBS) play a vital role in many smart building applications, enabling the creation of efficient and effective work environments. This study examines four memoryless positioning algorithms, namely K-Nearest Neighbour (KNN), Decision tree, Naïve Bayes and Random Forest regressor. The algorithms are compared based on their performance in terms of Mean Square Error, Root Mean Square Error, Mean Absolute Error and R^2. A comparative analysis has been conducted to verify the outcomes of different memoryless techniques in Wi-Fi technology. Based on empirical evidence, Naïve Bayes has been determined to be the localization strategy that exhibits the highest level of accuracy. The dataset containing the Received Signal Strength Indicator (RSSI) measurements from all the studies is accessed online.*

Keywords: RSSI, K-Nearest Neighbour, indoor localization, Random Forest Regressor

OBRAZOWANIE OPARTE NA CZĘSTOTLIWOŚCI RADIOWEJ DO LOKALIZACJI WEWNĄTRZ POMIESZCZEŃ Z WYKORZYSTANIEM TECHNIK BEZPAMIĘCIOWYCH I TECHNOLOGII BEZPRZEWODOWEJ

Streszczenie. *W ostatnim czasie Internet Rzeczy (IoT) rozwinął się i objął nadzór nad urządzeniami poprzez wykorzystanie Systemów Pozycjonowania Wewnętrznego (IPS) i Usług Lokalizacyjnych (LBS). Jedną z powszechnie stosowanych metod pozycjonowania wewnętrznego (IPS) jest wykorzystanie sieci bezprzewodowych do określenia lokalizacji celu. Osiąga się to poprzez wykorzystanie urządzeń o znanej pozycji. Usługi oparte na lokalizacji (LBS) odgrywają istotną rolę w wielu aplikacjach inteligentnych budynków, umożliwiając tworzenie wydajnych i efektywnych środowisk pracy. W niniejszym opracowaniu przeanalizowano cztery algorytmy pozycjonowania bez pamięci, a mianowicie K-Nearest Neighbour (KNN), drzewo decyzyjne, Naïve Bayes i Random Forest Regressor. Algorytmy są porównywane na podstawie ich wydajności pod względem błędu średniokwadratowego, pierwiastka błędu średniokwadratowego, średniego błędu bezwzględnego i współczynnika determinacji R^2. Przeprowadzono analizę porównawczą w celu zweryfikowania wyników różnych technik bez pamięci w technologii Wi-Fi. Na podstawie dowodów empirycznych ustalono, że Naïve Bayes jest strategią lokalizacji, która wykazuje najwyższy poziom dokładności. Zbiór danych zawierający pomiary wskaźnika siły odbieranego sygnału (RSSI) ze wszystkich badań jest dostępny online.*

Słowa kluczowe: RSSI, K-Nearest Neighbour, lokalizacja wewnątrz pomieszczeń, Random Forest Regressor

Introduction

The development of the Internet of Things (IoT) has resulted in the emergence of various novel applications, including location-based services, also known as localization. Localization is the act of adapting something to a specific geographic location, typically done through the utilization of Indoor Positioning Systems (IPS) and Location Based Services (LBS). Indoor localization is used to monitor patients in care facilities, supervise assets in warehouses, guide autonomous robots, and serve many other purposes. Localization is the method of accurately detecting the exact position of a target device by using measurements taken from certain fixed landmarks. The collection of prominent features used by the localization process is often known as the map. Traditionally, the Global Positioning System (GPS) has been the standard method for establishing localization in outdoor contexts. GPS utilizes satellites to determine the precise locations of the receivers. GPS signals are impeded by walls and roofs, rendering them unsuitable for indoor positioning. In an interior context, the existence of several reflections and obstructions poses more challenges in establishing a direct Line-of-Sight (LoS) connection between the transmitter and receiver, as opposed to an outside scenario. When selecting a localization mechanism for use in practical scenarios, it is vital to evaluate its scalability, cost-efficiency, installation prerequisites, and continuing expenditures.

Developing a globally applicable system to correctly monitor devices in various locations is not viable owing to many obstacles in localization. The variability of arrangements, dimensions, and impediments in different contexts necessitates that a system's effectiveness in one location may not translate to another. Therefore, while creating an indoor localization system, there is no simple answer. Acquiring a thorough understanding of the localization domain is crucial for achieving the best possible outcomes. This essay evaluates the efficacy of memoryless positioning algorithms and wireless technologies in three distinct circumstances. The choice of KNN, Naïve Bayes, Decision tree and Random Forest regressor was based on their widespread use in indoor localization systems that use fingerprinting and all are operating within the 2.4 GHz frequency band. The technologies were chosen based on their extensive use in smart city settings, prevalence in Internet of Things (IoT) applications, and simplicity in calculating the Received Signal Strength Indicator (RSSI) of received signals. The RSSI dataset obtained from the trials is accessible online [17].

1. Literature review

The selection of methodology used to compute the approximate location is a pivotal element in constructing a localization system. While trilateration is widely used in many systems due to its simplicity and scalability [18, 10], several systems choose to utilize fingerprinting as an alternative. Fingerprinting provides a notably greater level of precision, while it necessitates a longer duration for the establishment of the system [2, 8, 23, 26]. Comparative research was undertaken in [11] to assess three fingerprinting approaches, namely Bayesian, neural networks, and KNN. The study findings demonstrated that the K-nearest neighbours (KNN) approach attained the highest degree of accuracy, but at the cost of requiring the most extensive processing time for position determination. The rapid advancement of technology in recent years necessitates a greater investigation into innovative approaches. An thorough examination of the techniques and wireless technologies is necessary for determining the optimal selection for an indoor localization system utilizing fingerprinting.

The research done in [9] investigated several RSSI fingerprinting approaches, including Pompeiu-Hanusdorff distance, euclidean distance, and Kullback-Leibler distance. The study also evaluated the performance of both non-weighted and weighted KNN processing. The comparison was conducted with preexisting Wi-Fi access points. The suggested technique produced a wide range of results by using many testbeds in combination with experimental situations. The results suggested that algorithms with lower complexity produced more precise outcomes in comparison to those with greater complexity, whereas the precision of KNN only marginally increased.

Comparative research was conducted in [11] to assess the efficacy of two methods, Nearest-Neighbour and multi-trilateration, when implemented on a mobile device using Wi-Fi access points. The study showed that Nearest-Neighbour achieved higher accuracy than multi-trilateration. However, actual experiments have shown that using fingerprinting requires more processing resources, resulting in calculations with lower latency compared to multi-trilateration. Reducing latency is unfavourable in a real-time localization system since any delay in calculating results would be wasteful for tracking objects. The findings also indicated a negative link between the number of reference points and the level of accuracy. In order to improve the accuracy of the system, it is necessary to strengthen the selection process by selecting reference sites based on the minimum measured RSSI values from all available locations. Aside from the localization algorithm, the choice of wireless technology is also a crucial element to take into account in a localization system [20]. Wi-Fi is the dominant wireless technology used in localization systems, as shown by its extensive adoption [13, 24, 25]. Due to advancements in BLE technology, many systems are now prioritizing the use of BLE beacons [20] for indoor localization [12, 15, 16, 22]. Despite being less common than Wi-Fi or Bluetooth, Zigbee has gained attractiveness for IoT applications because to its low power consumption. It is progressively used for localization reasons [1, 8, 14]. Every technology has unique benefits and drawbacks when it comes to its application in localization. At present, there is inadequate study that compares various technologies in order to identify the most suitable and precise method of localization.

This study seeks to further explore the previously stated studies and provide a comparative analysis of two memoryless techniques: The efficacy of KNN and Linear regressor will be shown via three experimental scenarios to illustrate its usefulness in various contexts. To confirm the results, three wireless technologies - Zigbee, BLE, and Wi-Fi were used to evaluate their effect on accuracy and determine the best suitable method for an indoor localization system. This technology operated in the 2.4 GHz frequency region.

2. Signal inpainting methodology

In this situation, a range of surveillance equipment are strategically positioned in public areas such as security checkpoints, bank counters, and hallways to observe certain target areas. Generally, these places are furnished with Wi-Fi networks. Hence, the signals sent by different Wi-Fi access points that have been previously installed in the vicinity are employed. RF-Inpainter use the Received Signal Strength Indicator (RSSI) of Wi-Fi signals for the purpose of doing picture inpainting. Wi-Fi is the most advantageous option for RF broadcasts because to its extensive accessibility and cost-effectiveness. Public areas, such as offices, airports, and shopping malls, often have a substantial quantity of Wi-Fi access points (APs) already in place. This may significantly improve the accuracy of image inpainting. Currently, some imaging approaches that rely on Wi-Fi technology exploit certain features, such as CSI (Channel State Information), to generate pictures by identifying the multi-path aspects of radio channels [4, 6, 7]. Conversely, RSSI is used to measure the decrease in intensity of radio signals throughout their transmission, and it may be easily evaluated using commonly accessible wireless equipment. Therefore, the act of measuring RSSI is a more efficient and straightforward procedure. In order to achieve successful inpainting with RF-Inpainter, it is essential to use imaging methodologies that depend on the Received Signal Strength Indicator (RSSI) of Wi-Fi signals. In this work, four algorithms are proposed to inpaint the RF signal using the heatmaps. These algorithms vary in their methodology for representing connections between variables.

2.1. K-Nearest Neighbors (KNN)

When fingerprinting, KNN may be used to compare the RSSI results. A flowchart demonstrating the KNN process is shown in Figure 1. The received signal strength indicator (RSSI) values collected from access points in an unknown location are compared against the RSSI values recorded in the database using the Euclidean distance in a basic K-nearest neighbours (KNN) technique [5].

$$D_i = \sqrt{\sum_{j=1}^{n}(RSSI_{ij} - RSSI_j)^2},\ i = 1, 2, \ldots, M \tag{1}$$

The difference in distance between the recorded fingerprint (RSSIij) at location i and the measured RSSI value (RSSIj) at access point j of a test site is represented by the variable "Di". The number "n" indicates how many access points are kept in the database, while the number "M" indicates how many things are kept in the database. Calculating the distances between each point in the database and choosing the k closest matches are the steps involved in the procedure. The average of the (x, y) coordinates of these chosen matches is what yields the final result.

Algorithm:
1. Decide on the ideal neighbour size (K).
2. Calculate how far the new data point is from each and every other point in the dataset.
3. Compute the distances between each of the K closest neighbours.
4. The new data point should be classified into the class that has the highest frequency among its K closest neighbours. The value of a new data point in regression should be determined by averaging the values of its K closest neighbours.

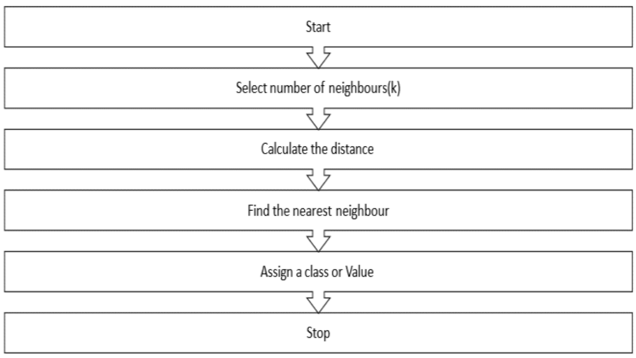

Fig. 1. Flow chart illustrates the KNN procedure [5]

2.2. Decision Tree model

The Decision Tree model is a widely-used machine learning approach employed for both classification and regression tasks. The process involves dividing the data into smaller groups based on the input feature values. The process is iteratively performed, leading to the creation of a hierarchical model composed of decisions. A Decision Tree is composed of nodes that create a hierarchical structure. This implies that it commences with a fundamental node and diverges into decision nodes and leaf nodes. A decision node contains multiple branches, with each branch indicating different attribute values that are being checked. Leaf nodes represent the final result or choice made after evaluating all qualities. The model asks a series of questions and makes decisions based on the answers. At each node, the model selects the attribute that effectively "splits" the data into subsets. The selection of attributes at each step is crucial and is typically done using metrics like Gini impurity, entropy (information gain), or variance reduction for regression trees.

Advantages of Decision Trees are easy to understand, visualize and interpret. They can handle both numerical and categorical data and can be used for both regression and classification tasks. Since Decision Trees do not assume any distribution of the data, they are considered non-parametric. This makes them flexible in handling real-world data. Decision Trees are used in various domains, including but not limited to, customer segmentation, fraud detection, investment decisions, and predicting sales or disease outbreaks. In summary, Decision Trees are a fundamental component of many machine learning algorithms, offering a foundation for more complex models like Random Forests and Gradient Boosted Trees. Their ease of use, interpretability, and versatility make them a popular choice for a wide range of problems.

2.3. Random-Forest model

The Random Forest Regressor is a widely used and flexible machine learning technique employed for regression problems, which include predicting a continuous value. It is a technique in machine learning that utilizes ensemble learning, which involves the combination of different models to enhance the overall performance. A Random Forest Regressor constructs numerous decision trees and combines their predictions to generate a more precise and consistent prediction. Random Forests can achieve great accuracy on diverse datasets by aggregating the predictions of several trees. This system has the capability to process a substantial amount of features and can accurately determine the significance of each feature in making predictions. This method is less prone to overfitting than individual decision trees due to the averaging of predictions. Random Forest Regressors are widely used in various fields, including finance for stock price prediction, medical for disease prediction, and energy for consumption forecasting, due to their versatility, ease of use, and robust performance across a wide range of data types.

Algorithm of Random-Forest tree:

1. Ensemble of Decision Trees: The Random Forest algorithm fundamentally constructs an ensemble of decision trees, typically trained using the "bagging" technique. Every tree inside the forest is constructed using a random subset of the training data, which is selected via replacement, also known as a bootstrap sample. The method is referred to as bootstrap aggregating or bagging.

2. Random Feature Selection: When growing each tree, Random Forest introduces additional randomness. When splitting a node, it selects a random subset of the features rather than the best split among all features. This ensures that the trees in the forest are diverse, which increases the overall model's robustness to overfitting.

3. Training Process:

i) For each bootstrap sample from the training data, a new decision tree is grown.

ii) A subset of features is selected at random for each node of the tree, and the optimal division is determined within this subset.

iii) This process is repeated until each tree reaches a predetermined size or no further splits can be made.

4. Prediction:

i) The Random Forest computes a forecast by combining the forecasts of every individual tree within the forest.

ii) This is typically accomplished for regression tasks by aggregating the predictions of all trees.

2.4. Naïve Bayes

The Naive Bayes model is a probabilistic approach in machine learning that is utilized for classification tasks. It relies on Bayes' theorem, which quantifies the likelihood of an event occurring, taking into account previous information about conditions that may be connected to the occurrence. The "naive" component of the model arises from the assumption that the features employed to forecast the target variable are mutually independent. Although simplified, Naive Bayes classifiers provide effective performance in numerous practical scenarios, especially in tasks such as document categorization and spam filtering. The benefits are the algorithm is characterized by its simplicity and efficiency, resulting in fast training and prediction. It demonstrates superior performance with limited data compared to other algorithms and is capable of handling both continuous and discrete data. The Naive Bayes model is a potent tool for various classification issues, especially in activities related to natural language processing (NLP) [5].

Key concepts of Naïve Bayes:

1. Bayes Theorem: At the heart of the Naive Bayes model is Bayes Theorem, which is used to calculate the posterior probability P(Y/X) of a class Y given predictors X shown in Eq. 2. The theorem is expressed as:

$$\mathrm{P(Y/X)} = \frac{P(X/Y)P(Y)}{p(X)} \tag{2}$$

The expression P(Y/X) represents the posterior probability of Y given X. Similarly, P(X/Y) represents the likelihood of X given Y. P(Y) denotes the prior probability of Y, while P(X) represents the prior probability of X.

2. Feature Independence: The Naive Bayes classifier operates under the assumption that the impact of a specific feature on a class is unrelated to the other characteristics. This assumption facilitates computing, and despite being a robust assumption, Naive Bayes models have demonstrated excellent performance in practical applications.

3. Model Training: During the training process, the model computes the likelihood of each class (known as the prior) and the likelihood of each class given each feature value (known as the conditional probability). These probabilities are utilized to construct forecasts on novel data.

4. Making Predictions: When dealing with a new instance, the model utilizes Bayes' Theorem to compute the posterior probability of each class based on the observed data. The class that has the highest posterior probability is considered as the expected outcome for the given case.

3. Experimental results

The RSSI (Received Signal Strength Indication) dataset contains 3 access points and 30 fingerprints collected in an indoor environment. It contains CSV files with RSSI values for each access point at different locations and the corresponding coordinates. These metrics provide a quantitative basis for comparing the performance of each model in inpainting the missing RSSI values. The Naive Bayes model shows the best performance across all metrics, indicating its higher accuracy and efficiency in predicting the missing values.

The RSSI dataset a simulated collection of Radio Signal Strength Indicator (RSSI) values, along with their corresponding (x, y) coordinates. RSSI values are typically used in wireless communication technologies to measure the power present in a received radio signal. In this case, the dataset seems to be simulated for a specific area, possibly representing a grid layout of a certain environment, such as a room or an outdoor area, where each (x, y) coordinate corresponds to a specific location within that grid, and the RSSI value represents the signal strength at that location.

The primary goal with this dataset seems to be demonstrating and evaluating different techniques for "inpainting" missing patches of RSSI values within the grid, using various machine learning models. This could be useful in scenarios where signal data is incomplete due to obstructions, non-coverage areas, or data collection issues, and there's a need to estimate the missing signal values based on the available data.

The differences between the inpainted grids of all models (KNN, Decision Tree, Random Forest, Naive Bayes) in terms of evaluation metrics (MSE, RMSE, MAE, R^2) reflect how each model performs in accurately predicting the missing RSSI values based on the surrounding data shown in Fig. 4, Fig. 5, Fig. 6 and Fig. 7 respectively.

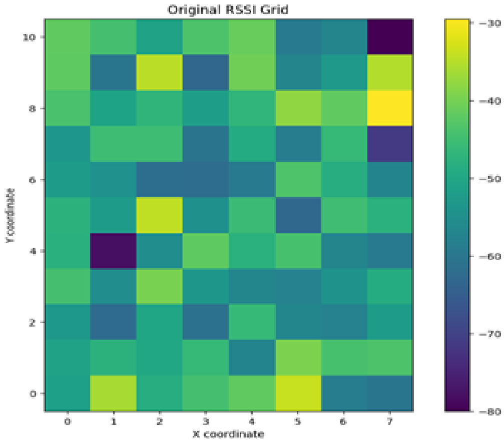

Fig. 2. Original RSSI grid [16]

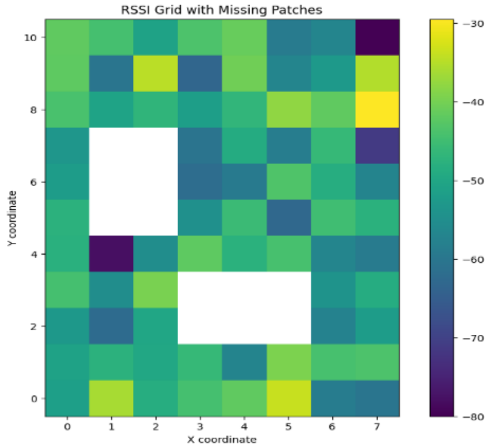

Fig. 3. RSSI grid with missing patches

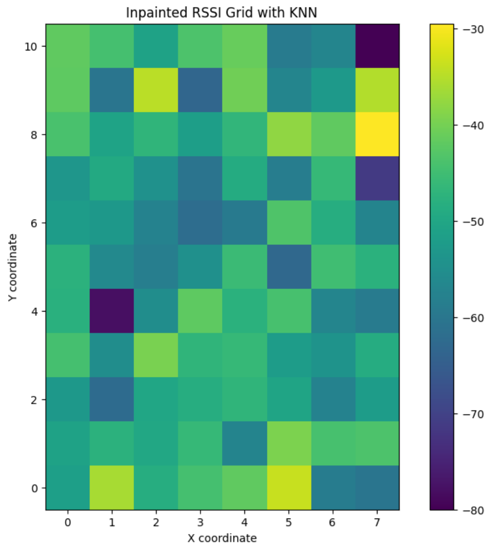

Fig. 4. Inpainted RSSI grid with KNN

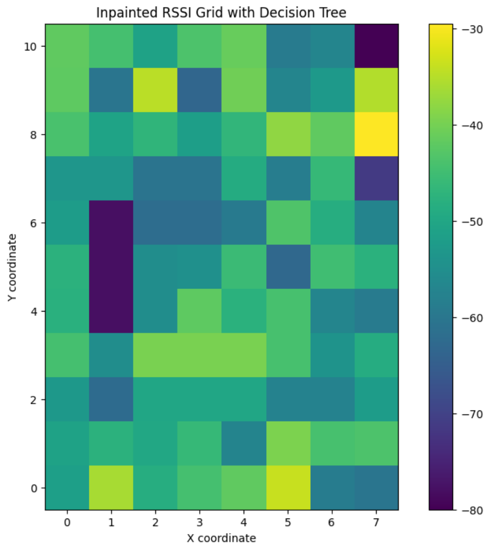

Fig. 5. Inpainted RSSI grid with Decision Tree

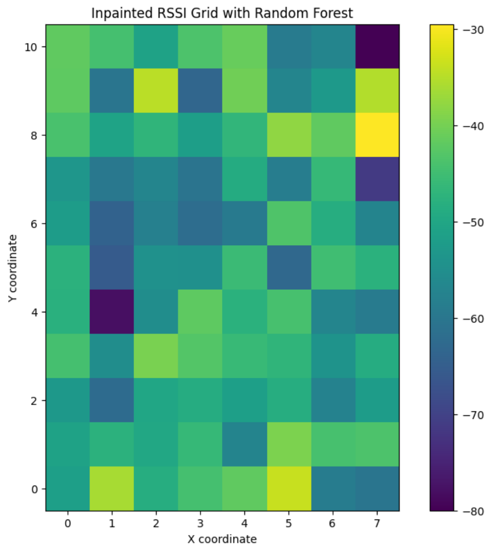

Fig. 6. Inpainted RSSI grid with Random Forest

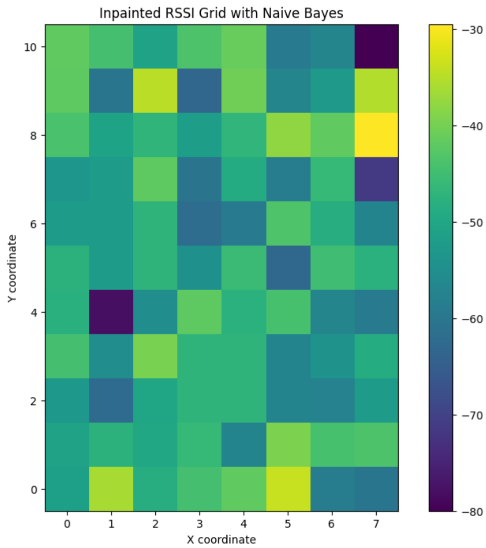

Fig. 7. Inpainted RSSI grid with Naïve Bayes

Here's a brief explanation based on the evaluation metrics:

1. Mean Squared Error (MSE) measures the average squared difference between the estimated values and the actual value. A lower MSE indicates a model that is more accurate in its predictions. In our comparison, the Naive Bayes model showed the lowest MSE, suggesting it was the most accurate in predicting the missing values.

2. Root Mean Squared Error (RMSE) is the square root of the MSE and provides a measure of the average magnitude of the error. Like MSE, a lower RMSE value indicates better model performance. Again, the Naive Bayes model outperformed the others by having the lowest RMSE, indicating its superior accuracy.

3. Mean Absolute Error (MAE) measures the average absolute difference between the predicted values and actual values, providing a linear scale of the errors made by the model. The Naive Bayes model had the lowest MAE, suggesting it made smaller errors on average compared to the other models.

4. R-squared (R^2) measures the proportion of the variance in the dependent variable that is predictable from the independent variable(s). An R^2 score closer to 1 indicates a model that explains a higher proportion of the variance. The Naive Bayes model had the highest R^2 score, indicating it was most effective in capturing the variation in the RSSI values.

Based on these metrics, the Naive Bayes model demonstrated superior performance in inpainting the missing RSSI values, showing the highest accuracy (shown in Fig. 8) and the least error compared to the KNN, Decision Tree, and Random Forest models shown in Table 1. This suggests that despite its simplicity and the assumption of feature independence, the Naive Bayes model was highly effective for this particular task of RF image inpainting.

Table 1. Quantitative analysis of different memoryless models

	KNN model	Decision Tree Model	Random Forest Model	Naïve Bayes Model
MSE	12.34	31.32	18.55	8.63
RMSE	3.51	5.6	4.31	2.94
MAE	1.0	1.75	1.49	0.81
R^2	0.85	0.62	0.78	0.90

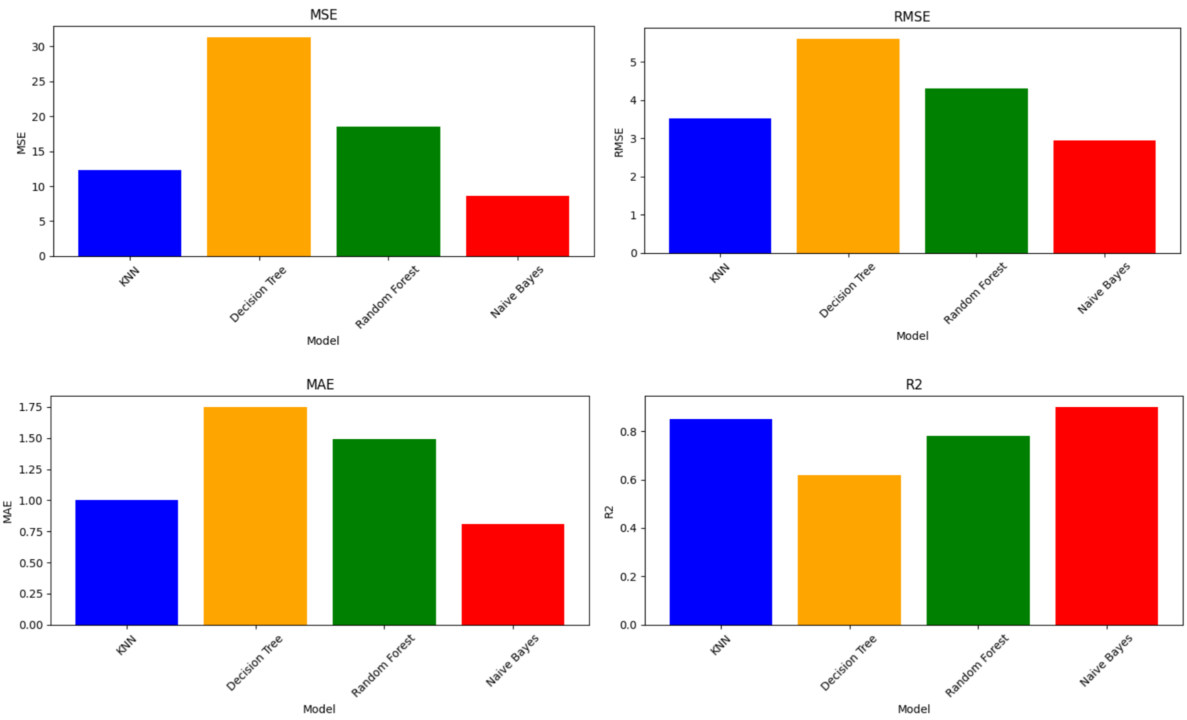

Fig. 8. Graphical Representation of Evaluation Metrics for inpainting models

4. Conclusion

The inpainting process explored various machine learning models to estimate missing RSSI values within a grid, simulating an RF image inpainting task. Each model brought its unique approach to the problem, leveraging the spatial and statistical properties of the dataset. The key findings from applying these models (KNN, Decision Tree, Random Forest, Naive Bayes) are summarized below:

KNN (K-Nearest Neighbors): This model predicted missing values based on the similarity to its 'K' nearest neighbors. It is straightforward and effective, especially when there's a strong spatial correlation in the data. However, its performance heavily depends on the choice of 'K' and the distance metric.

Decision Tree: The Decision Tree model approached the inpainting task by learning decision rules inferred from the data features. While it can capture complex patterns and relationships, it is prone to overfitting, especially in the case of a large depth.

Random Forest: As an ensemble of Decision Trees, the Random Forest model offered improved accuracy and robustness by averaging multiple decision trees' predictions. It managed to reduce overfitting and provided a more generalized solution, making it highly effective for the inpainting task.

Naive Bayes: Adapting the Naive Bayes model for inpainting was unconventional, given its typical use in classification tasks. By discretizing RSSI values and treating the problem as a classification task, the Naive Bayes model provided surprisingly accurate predictions, benefiting from its probabilistic approach and the assumption of feature independence.

The evaluation of these models based on metrics such as MSE, RMSE, MAE, and R^2 revealed that the Naive Bayes model, after adaptation, achieved the lowest RMSE, indicating high accuracy in predicting missing values. This suggests that, despite the simplicity and assumed feature independence, the Naive Bayes model was particularly effective for this task. The exploration of different inpainting techniques demonstrated that machine learning models could effectively estimate missing RSSI values, each with its strengths and limitations. The choice of model depends on the specific characteristics of the dataset, the desired balance between accuracy and complexity, and the underlying assumptions about data distribution and feature independence.

Using RF-Inpainter in computer vision tasks like object identification and moving path prediction might be a better way to evaluate its efficacy than depending just on metrics like mean PSNR and mean SSIM. This article highlights the potential of machine learning in addressing real-world problems in signal processing and spatial data analysis. In addition, future research will concentrate on improving picture inpainting and wireless transmission efficiency.

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