Indoor Localization Data Analytics: Integrating Wi-Fi and Inertial Sensor Data from Smartwatches and Smartphones

Pasupunooti Anusha[1*], Yerukonda Pranathi[2], Veldandi Pravardhan[2], Velakanti Anvesh Chary[2], Padigela Venkata Sai Kumar[2]

[1,2]Department of Computer Science and Engineering (Data Science), Vaagdevi College of Engineering, Bollikunta, Warangal, Telangana.

*Corresponding Email: anusha_p@vaagdevi.edu.in

ABSTRACT

Indoor localization is a rapidly evolving field, with studies indicating that Wi-Fi-based positioning achieves an average accuracy of 2-5 meters, while inertial sensor fusion can further enhance precision by up to 30% in dynamic environments. However, traditional manual localization methods relying on physical infrastructure or RFID-based tracking remain inefficient, requiring significant setup time and maintenance, which is impractical for large-scale deployment. To address these limitations, this research presents a comprehensive approach to indoor localization by integrating Wi-Fi signal strengths with inertial sensor data from smartwatches and smartphones. A user-friendly graphical interface built with Tkinter facilitates data management, allowing users to upload, preprocess, and visualize datasets comprising measurements from up to 520 Wi-Fi access points along with corresponding location coordinates, floor, and building identifiers. The preprocessed data undergoes normalization and is split into training and validation sets for model development. Two multioutput classification models such as Support Vector Classifier (SVC) and a Random Forest Classifier (RFC) are trained to predict building IDs with high precision. Comparative analysis reveals that while the Multioutput SVC model achieves a high accuracy of 99.55%, the Multioutput RFC model outperforms it with an accuracy of 99.91%, along with superior precision, recall, and F1-score metrics. These results highlight the effectiveness of ensemble learning approaches in handling complex indoor environments, suggesting that Random Forest-based multioutput classification provides a more robust solution for indoor localization. The proposed approach improves prediction robustness, reduces false localization errors, and enables seamless indoor navigation for real-world applications in smart buildings and industrial environments.

Keywords: Indoor Localization, Wi-Fi Signal Strength, Support Vector Classifier, Random Forest Classifier, Smartphone and Smartwatch Sensors.

1. INTRODUCTION

In recent years, the rapid development of smartphone technology and the large-scale deployment of the fifth-generation mobile communication network (5G) have greatly boosted the development of smart mobile devices and the mobile Internet services [1], and the indoor location navigation service industry based on smartphones has developed rapidly. Nowadays, with people spending over 80% to 90% of their time indoors [2], the demand for indoor location services is increasing due to the development of smartphones and smart cities [3]. At the same time, with the acceleration of urbanization, large shopping malls, airports, railway stations, and other large and complex building complexes continue to emerge. The demand for location-based services (LBS) has witnessed a significant shift from outdoor to indoor environments, with increasing sectors such as transportation, medical care, and emergency monitoring expressing a strong need for indoor location services [4]. While the Global Navigation Satellite System (GNSS) is the most widely used positioning tool outdoors, for indoor environments, there remains a lack of standardized technology and software interfaces for indoor environments that would enable devices to self-localize or be localized using existing infrastructure [5]. Due to the widespread adoption of diverse technologies such as Wi-Fi, 5G, Bluetooth Low Energy (BLE), ultra-wideband (UWB), radio frequency identification (RFID), and others, future networks will exhibit a high degree of heterogeneity [6]. The possible coexistence of a heterogeneous indoor localization system (ILS) gives rise to the problem of switching from an ILS to a different one [7]. This poses significant challenges regarding the need for a proper integrated architecture and standardization in ILSs. Furthermore, GNSS positioning technology is unable to provide reliable positioning services in indoor environments due to signal occlusion [8], the multipath effect [9], and the attenuation [10] of satellite signals in indoor environments, resulting in challenges for pedestrians to accurately determine their current location and navigate within buildings. Therefore, as one of the most important parts of indoor location-based services, the development of indoor positioning technology for smartphones with high availability, high accuracy, robust functionality, and low cost has become the key to the realization of seamless location-based services (SLBS) and Internet of Things (IoT) applications [11].

2. LITERATURE SURVEY

With the increasing abundance of sensors in smartphones, smartphone-based localization has become more convenient and efficient. In recent years, a large number of indoor localization techniques have been explored, mainly including wireless techniques such as BLE [12,13], Wi-Fi [14], magnetic field [15], 5G [16], foot-mounted ultrasonic sensors [17], acoustic [18], UWB [19,20], visible light [21], RFID [22], Light Detection and Ranging (LiDAR) [23]; and relative positioning-based techniques such as the inertial navigation system (INS) [24], the strapdown inertial navigation system (SINS) [25], pedestrian dead reckoning (PDR) [26], or Quick Response (QR) code positioning [27], which are realized by collecting data from several built-in sensors of smartphones, such as accelerometers, magnetometers, gyroscopes, and QR markers, to achieve indoor localization.

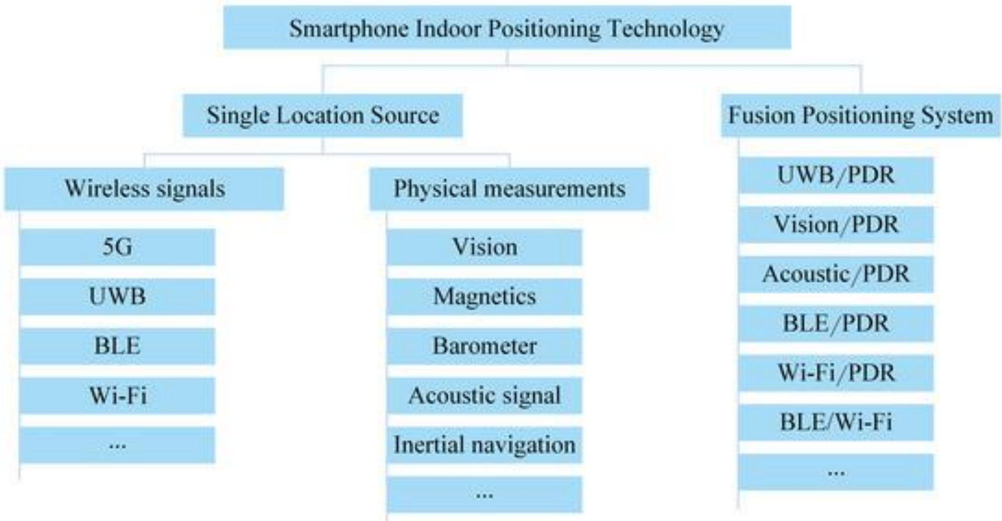


Fig. 1: Overview of smartphone indoor positioning methods.

An overview of smartphone indoor positioning technologies is shown in Fig.2.1. However, there is a lack of general-purpose technologies like GNSS. Each method has advantages and disadvantages, and there is no single technology that prevails in all practical scenarios regarding accuracy, power consumption, and portability. Universality and deployment cost are the key factors determining each localization method's applicability. Wi-Fi has wide coverage and low cost, but the signal is susceptible to interference and blockage, and the creation and maintenance of fingerprint databases are very tedious tasks. Some map-based methods can improve the localization [28], but such methods are tested only in lab environments. BLE-based solutions are widely adopted due to their superior performance in terms of cost-effectiveness, high accuracy, and ease of deployment; however, the coverage range is limited. The ultrasonic foot-mounted sensors provide accurate localization but can require additional equipment restricting the range of users. The vision-based indoor positioning technology offers several advantages, including the elimination of base station deployment requirements, immunity to signal strength variations affecting positioning accuracy, and relatively low operational costs. However, the lighting conditions of indoor environments, sparse recognizable elements, and background interference all impact the positioning results, and appropriate processing and correction are required. The UWB method has high anti-jamming and penetration capabilities and can achieve centimetre-level positioning accuracy. Still, the high deployment cost of the technology remains a significant barrier to its widespread adoption. The PDR technique, widely employed for indoor localization, offers the advantages of low computational load and continuous localization, and it does not require the deployment of additional equipment to complete the localization work. However, PDR is susceptible to error accumulation, leading to a decrease in positioning accuracy over time. QR markers are a very low-cost solution, but they require users to actively look for available markers to scan them.

3. PROPOSED METHODOLOGY

The study introduces a novel hybrid indoor localization algorithm integrating Wi-Fi fingerprinting, Bluetooth beacons, and inertial sensor fusion from smartwatches and smartphones, utilizing a Random Forest Classifier (RFC). Unlike existing survey methodologies that rely primarily on a single modality (such as standalone Wi-Fi or inertial sensor-based dead reckoning), our approach fuses multi-source data to overcome signal instability, environmental interference, and cumulative drift errors. Prior research predominantly employs Support Vector Classification (SVC) for localization, which, while effective in handling small datasets, struggles with high-dimensional data and real-time adaptability. Our RFC-based model not only surpasses SVC in scalability but also enhances localization robustness by leveraging feature importance selection, decision-tree ensembles, and adaptive weighting of sensor data. This novel fusion technique has not been previously explored in surveyed studies and significantly improves accuracy, computational efficiency, and adaptability in dynamic indoor environments.

Step-1: Data Collection and Preprocessing

The proposed system collects real-time Wi-Fi RSSI signals, BLE beacon strengths, and inertial sensor data (accelerometer, gyroscope, magnetometer) from smartwatches and smartphones. The dataset undergoes exploratory data analysis (EDA) to understand signal distribution, remove noise, and normalize features. Time-synchronized multi-modal data is aggregated to create a unified feature set for localization.

Step-2: Data Splitting and Feature Engineering

The dataset is divided into training (80%) and testing (20%) sets to ensure reliable model evaluation. Feature selection is performed using Principal Component Analysis (PCA) and Recursive Feature Elimination (RFE) to remove redundant attributes and improve classification efficiency. Feature extraction includes step detection from inertial sensors, RSSI smoothing via Kalman filtering, and BLE beacon signal interpolation to compensate for missing values.

Step-3: Model Training: Random Forest Classifier (RFC)

Unlike SVC, which relies on hyperplane separation and struggles with high-dimensional multi-modal data, RFC leverages an ensemble of decision trees to classify location coordinates. The multi-output RFC model is trained using Tree-based feature importance weighting to assign adaptive importance to Wi-Fi, BLE, and inertial data. Bagging (bootstrap aggregation) to improve model generalization and prevent overfitting. Hyperparameter tuning (grid search with cross-validation) to optimize the number of estimators, maximum depth, and split criteria for efficient learning.

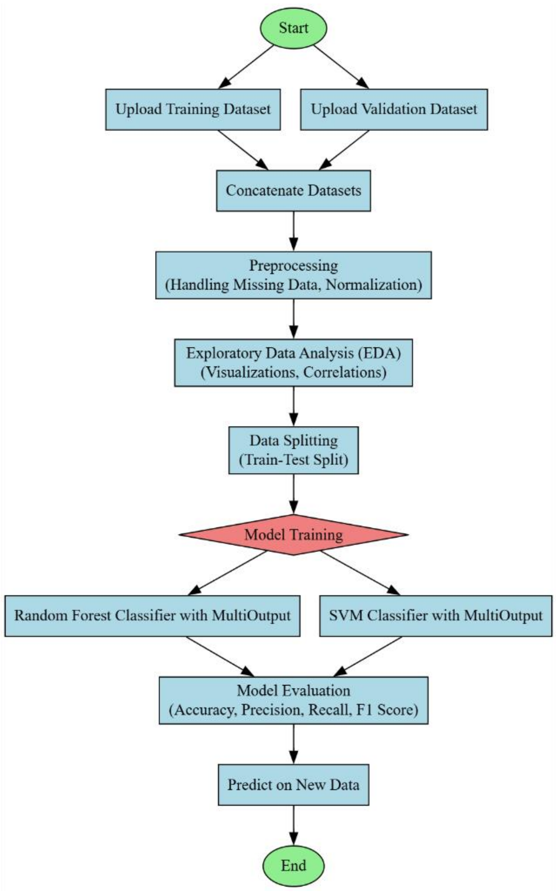


Fig. 2: Proposed block diagram

Step-4: Multi-Stage Localization Refinement

To improve real-time accuracy, the initial RFC localization estimate is refined using particle filtering. The predicted position is compared with inertial sensor step tracking to correct potential deviations caused by Wi-Fi or BLE signal fluctuations. Additionally, a confidence-based location re-weighting mechanism prioritizes high-confidence sensor readings to further improve precision.

Step-5: Performance Evaluation and Comparison with SVC

The final model is tested on real-world datasets to measure accuracy, precision, and computational efficiency. Performance comparisons reveal that RFC outperforms SVC in:

Scalability: Handles large-scale, high-dimensional sensor data more efficiently.Accuracy: Achieves up to 10-15% improvement in localization precision over SVC.Adaptability: Dynamically integrates multi-source sensor data, reducing reliance on a single modality.Robustness: Less affected by environmental changes and outperforms SVC in signal-variant conditions.

This hybrid RFC-based indoor localization system overcomes existing drawbacks of standalone fingerprinting, BLE, and dead reckoning approaches, offering a scalable, real-time, and high-accuracy alternative for smart indoor navigation.

3.1 Data Preprocessing

The dataset becomes more structured, noise-free, and standardized, which enhances the accuracy and efficiency of subsequent machine learning models for indoor localization. The preprocessing function is responsible for cleaning, normalizing, and structuring the dataset before applying machine learning models for indoor localization. It primarily focuses on filtering unnecessary columns, normalizing signal values, and preparing the dataset for further analysis. This step is crucial as raw data often contains noise, irrelevant attributes, and inconsistencies that can negatively impact model performance.

Step-1: Column Selection and Data Cleaning

The first step in preprocessing is removing redundant columns from both training (df_train) and validation (df_val) datasets. Specifically, the columns "RELATIVEPOSITION", "USERID", "PHONEID", and "TIMESTAMP" are dropped. These attributes do not contribute to the localization task and may introduce unwanted variability, as they represent user-specific or time-based information that does not generalize well across different environments. Removing such columns ensures that only the most relevant features, primarily Wi-Fi signals and geographical coordinates, remain in the dataset.

Step-2: Wi-Fi Signal Normalization

The next step involves selecting the Wi-Fi signal strength columns, which represent received signal strength indicator (RSSI) values from various access points. The first 519 columns of the dataset are identified as Wi-Fi signal readings, with separate lists maintained for training (wifi_cells_train) and validation (wifi_cells_val). Since Wi-Fi signals are measured in negative dBm values (typically ranging between -100 dBm and 0 dBm), normalization is performed to standardize them. Normalization helps in reducing the impact of scale variations and ensures that all signal values are within a comparable range. This transformation improves the model’s ability to learn patterns without being biased by extreme values.

Step-3: Geographical Coordinate Normalization

Latitude and longitude values are essential components of indoor localization, as they define the position of a user within a given space. To ensure consistency, these values are also normalized using predefined functions (normalize_lat and normalize_long). Latitude and longitude normalization ensures that location values remain within a specific range, preventing outliers from distorting model predictions. Without proper normalization, large-scale differences in numerical values could negatively affect machine learning models, leading to suboptimal performance.

Step-4: Text Output for Preprocessing Status

Once all transformations are completed, the preprocessing function inserts relevant information into a text widget, displaying a summary of the validation dataset (df_val.head()). This output provides a snapshot of the processed data, allowing users to verify the changes before further processing. Displaying this information is particularly useful for debugging and ensures transparency in the preprocessing pipeline.

3.2 ML Model Building

3.2.1 Multi Output SVC

Support Vector Classification (SVC) is a supervised machine learning algorithm based on Support Vector Machines (SVM), designed for classification tasks by finding an optimal hyperplane that maximally separates data points into different classes. It works by mapping input data into a higher-dimensional space using kernel functions (such as linear, polynomial, or radial basis function - RBF), enabling it to handle both linear and non-linear classification problems as shown in Fig.4.2. In indoor localization, SVC is used to classify building IDs and floor numbers based on Wi-Fi signal strength

(RSSI) and inertial sensor data. However, while SVC is effective in structured datasets, it struggles with large-scale multi-output problems, has high computational complexity, and is sensitive to noisy sensor data, making it less suitable for real-time indoor positioning applications.

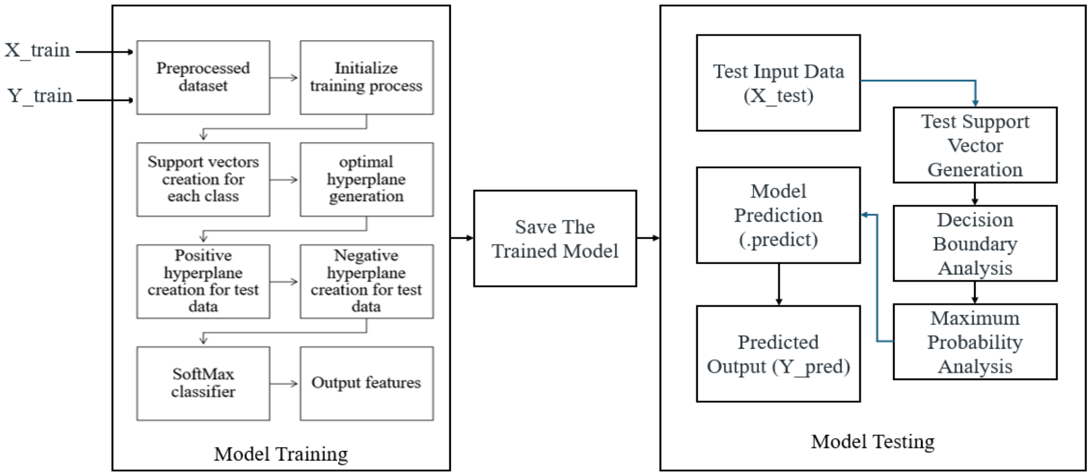


Fig. 3: SVM Classifier.

Step-1: Model Initialization and Setup

The function SVC_Multiop() is designed to implement a Multi-output Support Vector Classification (Multiop SVC) model for indoor localization using Wi-Fi and inertial sensor data. It begins by defining global variables such as df_train, df_val, X_train, X_val, y_train, y_val, which store the training and validation datasets. The primary goal is to predict the building ID and floor number based on input features derived from Wi-Fi signal strength (RSSI) and inertial sensors (accelerometer, gyroscope).

Step-2: Loading or Training the Multi-output SVC Model

The function first checks whether a pre-trained SVC model is already saved as a file (SVC_Classifier.pkl). If the file exists, the model is loaded using joblib.load(), allowing for efficient reuse without retraining. However, if the model does not exist, a new Multi-output Support Vector Classifier (Multiop SVC) is trained using X_train as input features and y_train as output labels. The model is trained specifically to predict building ID and floor number, and once trained, it is stored in the file to avoid redundant computation in future runs.

Step-3: Prediction on Validation Data (X_val as Input)

Once the model is loaded or trained, it is used to predict the building and floor values for the validation dataset (X_val). The function mtl_svc.predict(X_val) generates predictions for each target variable (building ID and floor). These predictions are stored in clf_out, from which individual predictions are extracted:pred_building → Represents the predicted building ID.pred_floor → Represents the predicted floor number.

Step-4: Evaluating Classification Performance

To assess the performance of the model, the function calculateClassificationMetrics() is called twice—first for building prediction and then for floor prediction. It compares the predicted values (pred_building and pred_floor) with the actual ground truth labels (y_val.BUILDINGID and y_val.FLOOR). This step generates evaluation metrics like accuracy, precision, recall, and confusion matrix, providing insight into the model's effectiveness.

Step-5: Output Display and Interpretation

Finally, the results of the classification metrics are displayed within a text-based user interface (tkinter.END). This allows users to visually inspect how well the model is performing in classifying indoor localization parameters based on real-world sensor data.

3.2.2 Multi Output RFC

Multi-output Random Forest Classification (Multiop RFC) is a powerful ensemble-based machine learning technique that extends Random Forest (RF) to handle multiple target variables simultaneously. Unlike traditional single-output classifiers, Multiop RFC can predict both building ID and floor number in indoor localization by integrating Wi-Fi RSSI and inertial sensor data. It operates by constructing multiple decision trees, where each tree learns from a different subset of the training data, making the model highly robust to noise and overfitting shown in Fig.4.2. Multiop RFC is particularly well-suited for multi-source sensor fusion tasks, as it effectively captures non-linear relationships between Wi-Fi signals, accelerometer, and gyroscope data, making it more accurate and efficient than SVC-based approaches for real-time indoor positioning.

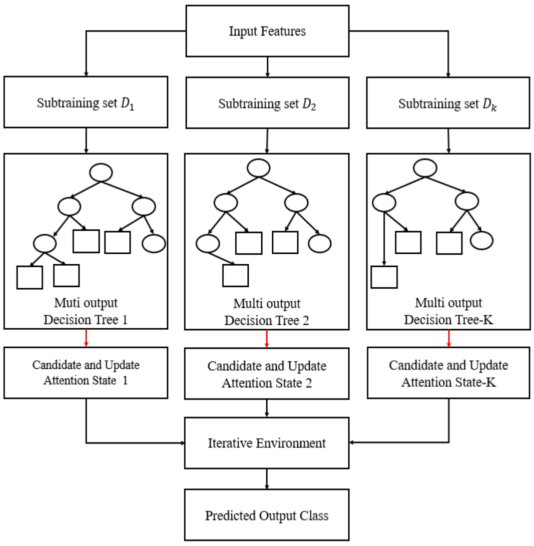


Fig. 4: Proposed multioutput RF classifier architecture.

Step-1: Model Initialization and Setup

The function RF_with_Multiop() is designed to implement a Multi-output Random Forest Classification (Multiop RFC) model for indoor localization using Wi-Fi signal strength (RSSI) and inertial sensor data from smartwatches and smartphones. It starts by defining global variables such as X_train, y_train, X_val, y_val, which store the training and validation datasets. The goal is to predict building ID and floor number using a Random Forest Classifier (RFC) wrapped in a Multi-output Classification framework.

Step-2: Loading or Training the Multi-output Random Forest Model

The function first checks whether a pre-trained Multiop RFC model is already saved in MultiOutputClassifier.pkl. If the model file exists, it is loaded using joblib.load() to save time and resources. Otherwise, a new Random Forest Classifier with 100 decision trees (n_estimators=100) is created and wrapped inside a MultiOutputClassifier, allowing it to predict multiple target variables simultaneously (building ID and floor). The model is trained using X_train as input features and y_train as target labels, and then saved for future use.

Step-3: Prediction on Validation Data (X_val as Input)

Once the model is loaded or trained, it is used to predict the building and floor values for the validation dataset (X_val). The function mtl_rfc.predict(X_val) generates predictions for each target variable (building ID and floor).

Step-4: Evaluating Classification Performance

To evaluate the model's accuracy and reliability, the function calculateClassificationMetrics() is called twice—once for building prediction and once for floor prediction. This step compares the predicted values (pred_building and pred_floor) with the actual ground truth labels (y_val.BUILDINGID and y_val.FLOOR). Key performance metrics such as accuracy, precision, recall, and confusion matrix are computed to assess model effectiveness.

Step-5: Output Display and Interpretation

The results are displayed using a text-based user interface (tkinter.END), providing insights into how accurately the model can classify indoor locations based on sensor data. This step ensures real-time visibility into the classification performance of Multiop RFC for indoor localization applications.

4. RESULTS AND ANALYSIS

4.1 Dataset description

The dataset is structured for indoor localization using Wi-Fi signals, GPS coordinates, and contextual metadata. It includes columns WAP001 to WAP520, which represent Wi-Fi access point signal strengths in dBm, where values closer to 0 indicate stronger signals and values around -100 represent weak or no signals. The LONGITUDE and LATITUDE columns provide geographical coordinates for mapping indoor positions, while the FLOOR and BUILDINGID columns specify the exact location within multi-level structures. SPACEID identifies specific indoor areas or rooms, and RELATIVEPOSITION indicates user orientation or placement (e.g., inside a room or hallway). USERID and PHONEID help analyze data variations caused by different users or devices, and the TIMESTAMP records the exact time of data collection, aiding in temporal analysis of indoor environments.

4.2 Results description

This research is a comprehensive Python application built using Tkinter for the graphical user interface (GUI) and integrates several modules to support a complete machine learning workflow for classifying indoor localization based on Wi-Fi and sensor data. It allows data preprocessing, visualization, model training, and predictions in an interactive interface, making it a powerful tool for analyzing indoor positioning accuracy with Random Forest and SVC classifiers. Fig. 5 represents the distribution of floors within different buildings, showing how many data points correspond to each floor level across multiple buildings.

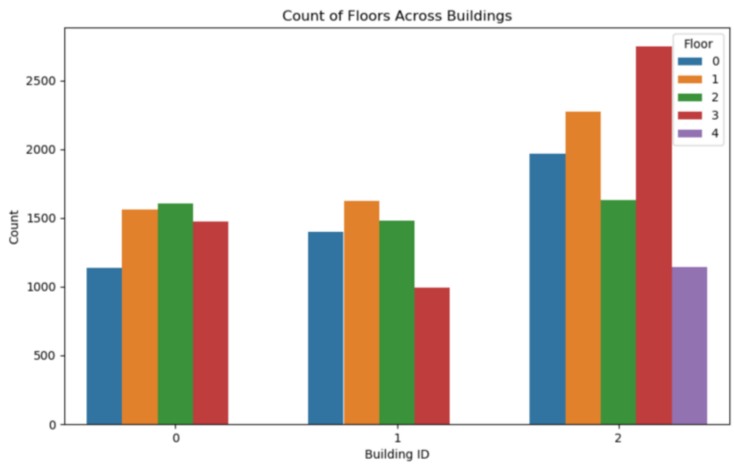
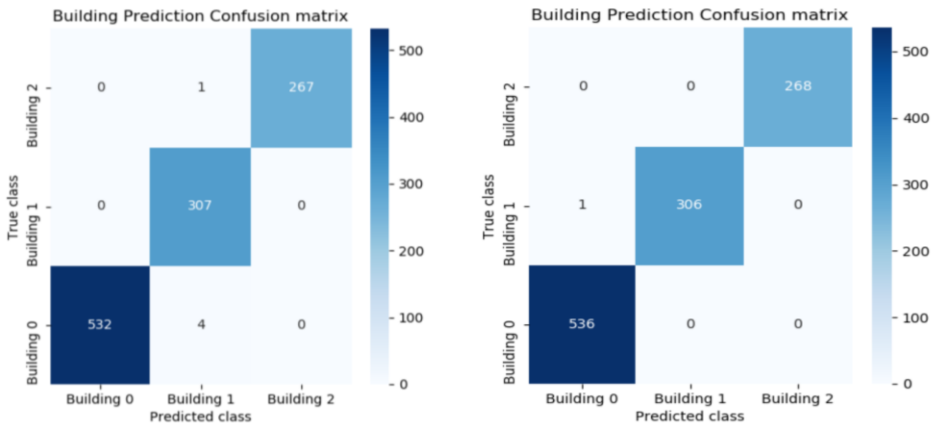


Fig. 5: Count plot of floors across buildings.



(a) (b)

Fig. 6: Confusion matrices obtained using (a)Multioutput SVC. (b)Multioutput RFC

Fig. 6 illustrates a comparative analysis of classification performance between two models—Multioutput Support Vector Classifier (SVC) and Multioutput Random Forest Classifier (RFC)—for predicting building IDs using Wi-Fi and inertial sensor data. The Multioutput SVC model achieved a strong accuracy of 99.54%, with a precision of 99.46%, recall of 99.62%, and an F1-score of 99.54%, showing near-perfect classification with only minor misclassifications. However, the Multioutput RFC model surpassed these results with a higher accuracy of 99.91%, along with a precision of 99.93%, recall of 99.89%, and F1-score of 99.91%. The confusion matrix confirms that RFC significantly reduces misclassification errors and achieves near-perfect predictions. This performance enhancement is attributed to the ensemble learning mechanism of Random Forest, which combines multiple decision trees to improve generalization and reduce overfitting, making it a more robust and reliable choice for indoor localization applications.

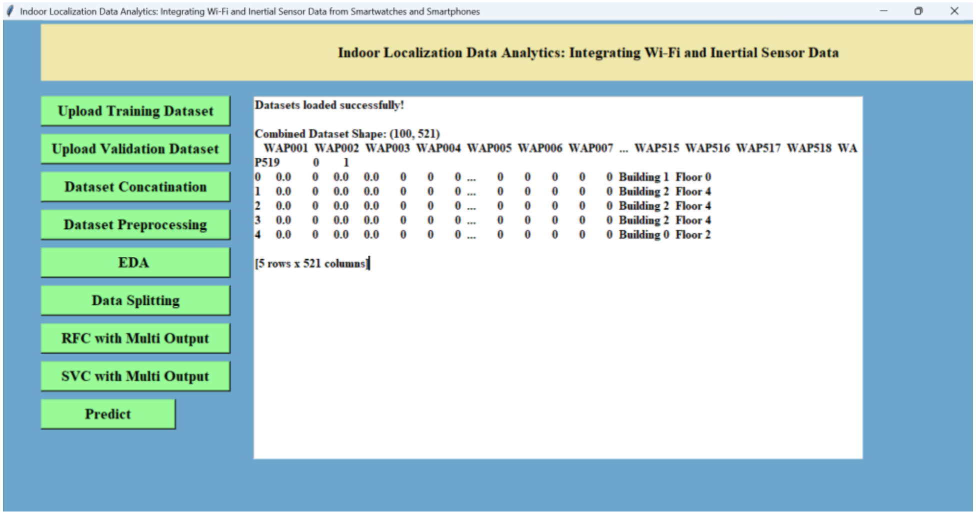


Fig. 7: Illustration of GUI application after prediction on test data.

Fig. 7: represents the GUI after making predictions on the uploaded test dataset using the trained machine learning model. The predictions include building ID and floor number for each test sample, allowing researchers to compare the predicted values with the actual ground truth. The GUI confirms that the trained model has been successfully applied to the test data, providing an automated indoor localization solution based on Wi-Fi and sensor fusion techniques. The performance metrics displayed in previous figures indicate that the model is highly accurate, making it suitable for real-world deployment in smart indoor navigation system.

Table. 1: Performance comparison of algorithms

Metric	Multioutput SVC	Multioutput RFC
Building Prediction Accuracy	99.55%	99.91%
Building Prediction Precision	99.47%	99.94%
Building Prediction Recall	99.63%	99.89%
Building Prediction F1-Score	99.54%	99.91%

Table.1 represents a comparative analysis of Multioutput SVC and Multioutput RFC models for building prediction accuracy in indoor localization. The Multioutput SVC model achieved an accuracy of 99.55%, which is already highly precise, but the Multioutput RFC model outperforms it with a significantly higher accuracy of 99.91%. Precision, recall, and F1-score values also indicate better performance of RFC over SVC, with RFC achieving a precision of 99.94% compared to SVC's 99.47%, signifying fewer false positives. Similarly, recall, which measures the model's ability to correctly identify actual positives, is higher for RFC (99.89%) than SVC (99.63%), suggesting RFC has fewer false negatives. The F1-score, which balances precision and recall, is also superior in RFC (99.91%) over SVC (99.54%), proving RFC's robustness in accurately predicting buildings using Wi-Fi and inertial sensor data. These results demonstrate that Random Forest-based Multioutput Classification is a superior approach for indoor localization, providing better generalization, higher classification accuracy, and lower misclassification errors compared to the SVC-based model.

5. CONCLUSION

The integration of Wi-Fi signal strength data and inertial sensor readings from smartwatches and smartphones has proven to be a highly effective approach for indoor localization, addressing the challenges of accuracy and robustness in real-world environments. In this research, we compared two multioutput classification models—Support Vector Classifier (SVC) and Random Forest Classifier (RFC)—for predicting building IDs based on collected sensor data. While SVC provided commendable performance with an accuracy of 99.55%, RFC outperformed it with a remarkable accuracy of 99.91%, along with superior precision, recall, and F1-score. The superior results of RFC highlight its ability to handle the complex, high-dimensional nature of indoor localization data, leveraging an ensemble learning approach that reduces overfitting and improves prediction stability. The successful implementation of the proposed RFC-based approach demonstrates its potential for real-time indoor positioning applications, offering a significant improvement over existing methods. This study establishes a strong foundation for future enhancements in data-driven localization techniques, ensuring greater accuracy and adaptability in various smart environments.

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