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AGFiLoc: Adaptive Geolocation using Wireless Fidelity for Localization

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ABSTRACT

User presence detection and movement pattern recognition are primary factors that impact the accuracy and reliability in indoor positioning of dynamic users in Wireless Fidelity (Wi-Fi) systems. Although several models have been proposed to improve the set factors, occupancy characterization, which is largely based on device behavior, still impacts the reliability and accuracy of the results obtained. In this paper, an Adaptive Geolocation using Wireless Fidelity for Localization (AGFiLoc) model is proposed. and its performance in improving reliability of user presence detection and movement pattern recognition is compared against the performance of existing models. The developed AGFiLoc model applies sliding window analysis for user presence detection, while a combination of ARIMA and DBSCAN were utilized for the movement pattern recognition of users. Additionally, decision trees machine learning model was used to extend the AGFiLoc models application in dynamic environments.

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Furthermore, a ε-differential privacy technique was adopted to protect individual's data within a dataset. The performance of the proposed AGFiLoc model was compared against MLUPPBALS and CSIHBSRCFI models, while considering accuracy, precision, sensitivity, F1-score, latency, and computational efficiency as performance metrics. With respect to the existing MLUPPBALS and CSIHBSRCFI models, AGFiLoc achieved an 8.24% and 4.55% improvement in accuracy, a 9.88% and 7.23% improvement in F1 score, a 20% and 14.29% improvement in latency, and a 21.43% and 13.33% in computational efficiency. Additionally, the precision and sensitivity the AGFiLoc model respectively showed a 9.79% and 10% improvement against the MLUPPBALS model, and it respectively showed a 5.88% and 4.76% percentage improvement against the CSIHBSRCFI model.

***Keywords*:** Data privacy, Movement pattern recognition, User presence detection, Wireless Fidelity, Occupancy characterization

1. INTRODUCTION

The established Wireless Fidelity (Wi-Fi) infrastructure and off-the-shelf user devices that are Wi-Fi enabled has established an affordable, scalable, and flexible indoor positioning system for Wi-Fi localization (Adikpe *et al*., 2022). The diversified application of this infrastructure is adapted in multiple literature for indoor positioning of users. However, the dynamic characterization of occupant in these diverse spaces, which could be offices, campuses, hospitals, among others, impacts the accuracy and reliability of Wi-Fi localization. This challenge that arise in these spaces are a consequence of factors such as multipath effects, signal attenuation, and the dynamicity of environmental settings (Hao *et al*., 2020, Liu *et al*., 2020; Yang *et al*., 2021; Jiang *et al*., 2021; Adikpe *et al*., 2022; Yang *et al*., 2023, Adikpe et al., 2023).

To address the aforementioned challenges, several Wi-Fi-based localization models leverages Received Signal Strength indicator (RSSI) to estimate the position of users (Gupta *et al*., 2020; Trivedi *et al*., 2021; Dmitrienko *et al*., 2020; Li *et al*., 2021). Generally, the RSSI-based approach utilizes the power level of received signals to determine the distance between Access Points (APs) and the User Equipment (UE) of users (Bay *et al*., 2020; Jiang *et al*., 2021, Adikpe *et al*., 2022; Farahsari *et al*., 2022). However, the readings are highly vulnerable to interference by other RF-based devices, fluctuations by obstacles, and dynamic nature of indoor environments – all of which can affect the accuracy and reliability of localizations results.

On this premise, this paper introduces Adaptive Geolocation using Wireless Fidelity for Localization (AGFiLoc) as a model to enhance the accuracy and reliability of RSSI-based localization systems. The AGFiLoc model uses the enhanced localization system to improve the reliability of user presence detection and movement pattern recognition in a dynamic environment setting. The developed AGFiLoc model applies sliding window analysis for user presence detection. The sliding window analysis separates the data from the RSSI into manageable durations to detect the presence of users. Also, it continuously updates the information learned from its environment. Additionally, a combination of ARIMA and DBSCAN are utilized for the movement pattern recognition of users. Moreover, decision trees machine learning model are used to extend the AGFiLoc models application in dynamic environments. Furthermore, a ε-differential privacy technique was adopted to protect individual's data within a dataset. The performance of developed AGFiLoc model is primarily compared against existing models considering accuracy, precision, sensitivity, F1-Score, latency, and computational efficiency as performance metrics. The AGFiLoc model is observed to outperform the existing models.

For the remaining part of this paper, Section 2 review recent literature that focus on adaptive localization with emphasis on dynamic occupancy characterization of users. Section 3 delineates the methodology adopted to develop the Adaptive Geolocation using Wireless Fidelity Localization (AGFiLoc) model. The results and discussion of the proposed model against existing models are presented and discussed in Sections 4 and 5, respectively. Section 6 concludes this paper.

2. LITERATURE REVIEW

A review of recent literature that emphasis on adaptive localization of users with a focus on the dynamic occupancy characterization of users are discussed hereunder.

The work of Jiang *et al*., (2019) presented a Wi-Fi-based HAR system that improved the recognition accuracy of the model by utilizing the hierarchical relationship between activities. An activity-oriented process was developed to adopted to extract selected features based on hierarchical structure of activities and designed a layer-structured classification architecture. The development of the model required the training of classifiers using selected features connected to the environmental activities. Simulation results showed significant performance in terms of accuracy and sensitivity amidst changes in the environment. The drawback of the system is its dependency on defined physical relationships between activities, which can limit its wide range application.

The work of Feng *et al*., (2019) proposed a model for recognizing human activity using CSI from off-the-shelf Wi-Fi UEs. The work was achieved in three stages to account for the size of the training samples. The first stage which was for small sample sizes, used DTW. The second stage, for moderate sample sizes, used SVM, while the third used LSTM for large sample sizes. Results showed accuracy that balanced accuracy and efficiency. The drawback of the model could face challenges in noisy environments with multiple subjects due to the complexity of identifying different activities.

The work of Jiang *et al*., (2021) presented a model for estimating the position of users in shopping malls. It utilized the combined data obtained from UEs, GPS, and Wi-Fi. An XGBoost model was modified into two layers. The first layer estimated the location of UEs within various shops by addressing a multi-class problem. The second layer modified the prediction into a binary classification. Several features like the Wi-Fi signal, environment, and the transaction records of users in shops were used to train the model. Simulation results showed that the XGBoost model modified by the authors showed better accuracy and precision results in comparison to existing KNN algorithm and the statistical rule-based algorithm. Although, the potential introduction of outliers from the GPS data can impact localization accuracy and precision.

The work of Bu *et al*., (2022) proposed a method of identifying gestures via deep transfer learning on Wi-Fi signal CSI. The method captured CSI streams during gesture performance to transform the 1-D signals into 3-D images. The deep CNNs were applied for classification. Two approaches were adopted. These are high-level features extracted by deep CNN and fine-tuned CNN model that was pre-trained. The dataset of 12 different gestures were used to test the system in an indoor environment. The system outperformed existing systems tested against. However, the model suffered from overfitting due to large number of parameters in fully connected layers.

The work of Yang *et al*., (2023) developed a model for human behavior segmentation and recognition using CSI from off-the-shelf Wi-Fi UEs. Supervised learning algorithm was used to segment the data collected on the behavior of the UEs into understandable segments in order to distinguish the behaviours through the model. A developed segmentation algorithm and a CNN network for classification were combined to implement the system. Simulation results showed a successful identification of several UE behaviours to the potential of the model for non-intrusive behavior monitoring. Nonetheless, the drawback was primarily on the volume of data needed to train the CNN, which could increase the computational cost.

The work of Arora *et al*., (2024) presented a model that utilized the historical trajectory data to determine the future location of mobile UEs. The clustering historical trajectories using BIRCH algorithm was utilized to represent the data within dense regions. A BiLSTM model was trained to determine the future position of UEs within each cluster. A classifier used to determine the most similar data from clusters when a trajectory was considered. Additionally, the BiLSTM model was used to predict other locations. Simulation results showed that the model enhanced the prediction accuracy of user in comparison to other existing methods. The drawback was the computational cost of training multiple BiLSTM models.

While the models achieved their aim in increasing the accuracy of user presence detection and mobility pattern recognition, a major drawback that still persists is the computational cost in implementing the existing models. On this premise, the AGFiLoc model not only work in improving the aforementioned factors but also improves the computational cost of the process.

3. METHODOLOGY

The steps carried out to develop, implement, and evaluate the AGFiLoc model for user presence detection and movement pattern recognition are delineated hereunder:

3.1. Data Collection

The data collected in this step are the Wi-Fi signal and the user behavior. For the Wi-Fi signal, the data from the RSSI from the strategically placed Wi-Fi APs to the UEs are collated. This process includes logging the MAC addresses of the devices, timestamps of each recorded signal strength, and the identifiers of the APs. These data is used to estimate the distance between the APs and the UEs. The data collected is used for analyzing position and movement pattern of UEs within the coverage area. The data collected on user behavior helps with understanding how users interact with their UEs. On this premise, data on the time frame and frequency of UE usage, movement pattern within the coverage area of interest, and idle time when the device is inactive are factors considered in determining the user's interaction with their UEs. This data helps with segmenting the UEs that are stationary and idle, stationary and active, mobile and idle, and mobile and inactive. This layer of context helps in determining the presence of users.

3.2. Device Behaviour Analysis

Movement pattern recognition and user presence detection are key factors considered in device behavior analysis.

3.2.1. Movement Pattern Recognition

The data gathered of the RSSI value over a defined time frame is analyzed to determine the stationarity or mobility of UEs. To address the fluctuations that introduces outliers to the information gathered, the AGFiLoc model utilizes the Autoregressive Integrated Moving Average (ARIMA) time series methods to track subtle changes in RSSI values. ARIMA's ability to handle non-stationary data through differencing makes it ideal for RSSI values. Additionally, it provides short-term forecasts which is necessary for recognizing the movement pattern of UEs. Additionally, a Density Spatial Clustering of Applications with Noise (DBSCAN) is used to detect segments of RSSI values that share similarities with a different locations or other movement patterns. The DBSCAN helps in distinguishing patterns that are irregular, handling noise and outliers in the data, which are common in Wi-Fi signal data. Also, the adaptability of DBSCAN does not require a specific number of clusters before deployment, which makes it flexible for different environments and movement patterns. The combined ARIMA and DBSCAN for time analysis and clustering, respectively, enables the AGFiLoc model to improve movement pattern recognition, which is crucial for user presence detection.

3.2.2. User Presence Detection

The movement pattern recognition is further enhanced by sliding windows for window analysis, as this gives the AGFiLoc model the ability to continuously monitor and analyze Wi-Fi data in real-time, which is necessary for user presence detection. A major characteristics of sliding windows is its overlapping nature, where a fixed-length window moves incrementally over the dataset. This feature ensures that data points are not missed between consecutive analyses which increases the reliability of user presence detection. This constant stream of data analyzed by the sliding window can in real-time, identify changes in signal strength to indicate the stationarity or mobility of a user, which is necessary for identifying the presence of a user and the users movement pattern. Additionally, the sliding windows aid in smoothing the data and mitigating the impact of noise to obtain a detection outcome with higher accuracy. Features such as average RSSI and variance are computed to differentiate the varying stationarity or mobility states of users. A decision tree algorithm is trained on labelled data and applied to classify the varying states of users.

RSSI filtering is achieved using (1):

$$RSSI_{filtered} = \alpha . RSSI_{current} + (1-\alpha) RSSI_{previous} \tag{1}$$

where α represents the smoothing factor (0< α<1)

The presence detection pseudocode is delineated hereunder:

User Presence Detection Pseudocode

```
function sliding_window_detection(rssi_data, window_size, step_size, model)
   Initialize user_presence as an empty list
   Calculate num_windows as (length of rssi_data – window_size) / step_size + 1
   for I from 1 to num_windows
      start_idx = (i-1) * step_size + 1
      end_idx = start_idx + window_size – 1
      window_data = rssi_data[start_idx:end_idx]
      Append presence_state to user_presence
      features = extract_features(window_data)
      presence_state = predict(model_features)
   return user_presence

function extract_features(window_data)
   mean_value = mean(data)
   return sum((x-mean_value)^2 for each x in data) / (length(data)-1)

function slope_of_linear_fit(data)
   n-length(data)
   x = array of indices from 1 to n
   y = data
   x_mean = mean(x)
   y_mean = mean(y)

   num=sum((x[i]-x_mean) * (y[i] – y_mean) for I from 1 to n)
   den = sum((x[i] – x_mean)^2 for I from 1 to n)
   return num / den

function predict(model, features)
   #Assuming a pre-trained decision tree model
   #This function takes the extracted features and predicts the presence state
   presence_state = model.predict(features)

   return presence_state
```

3.2.3. Anomaly Detection and Handling

The fluctuations in RSSI values may indicate that a user has either moved outside the Wi-Fi range or the UEs of the user has been temporarily disconnected. Moving average filters is adopted to smooth out the RSSI data making it easier to detect abrupt changes. Additionally, setting up timers to determine short periods that account for factors like interference or the out of range activity of the UE that may cause the UE to temporarily lose connection in necessary to manage brief disconnections.

However, if the users UE reconnects within this time frame, the user is assumed to still be present in the network. This mitigates false negatives and false positives that may affect the data on the position of the user. The moving average filter is obtained using (2):

$$\textbf{(2)} \quad RSSI_{avg} = \frac{1}{N}\sum_{i=0}^{N-1} RSSI\left(t-1\right)$$

where N denotes the window size

3.2.4. Machine Learning

For this paper, the decision tree ML model is adopted. This model is pre-trained on labelled data to classify the states of devices. The model uses features derived from RSSI values, user behavior data, and contextual information to predict whether a device is stationary, moving, or temporarily disconnected. The decision trees ML model was selected due to its ability in handling non-linear relationships, missing data, and outliers. And the computational cost is less when compared to models such as neutral networks and Support Vector Machines (SVM). Also, the contextual information like user behavior pattern, time, and location-specific data are combined to improve the accuracy of AGFiLoc model in detecting the presence of users. The expression for the decision tree is delineated hereunder in (3):

$$\textbf{(3)} \quad f\left(x\right) = \sum_{i=1}^{n} \alpha_i y_i K\left(x_i, x\right) + b$$

where K represents the kernel function, $\propto_i$ denotes the Lagrange multipliers, y_i delineates the labels, and b signifies the bias term.

3.2.5. Data Anonymization and Privacy Protection

A hashing MAC data anonymization technique is applied in the AGFiLoc model to protect user privacy. In this case, the Personally Identifiable Information (PII) of user are replaced with pseudonyms. These pseudonyms become the new user identifiers. Anonymization ensures that the collected data cannot be back traced to the UEs of individual users. This aids in addressing privacy concerns and complying with data protection regulations. The core of every privacy protection scheme centers on anonymizing data without compromising the accuracy. The ε-differential privacy techniques is used in this paper to protect the data of individuals within a dataset. This technique adds control noise to the data to protect the users data. The ε-differential privacy technique enhances the AGFiLoc model as it stabilities the demand for user presence detection that is accurate with protecting the privacy of users. This is expressed hereunder in (4):

$$\textbf{(4)} \quad \varepsilon\text{–}differential\ privacy: \Pr\left[A\left(D'\right) \in S\right] \leq e^{\epsilon} \Pr\left[A\left(D\right) \in S\right]$$

where ε delineates a non-negative parameter that measures the privacy loss
A denotes a randomized algorithm for processing and analyzing data.
$D\ and\ D'$ signifies the datasets that differ by only one element
S outlines possible output space
e^{ϵ} represents a multiplicative bound that determines how much likely the algorithm A produces a definite output when applied to $D\ verses\ D'$.
$Pr[\mathrm{A}(D) \in S]$ characterizes the probability that A produces an output within the set S when applied to dataset D.
$Pr[\mathrm{A}(D') \in S]$characterizes the probability that A produces an output within the set S when applied to dataset D'.

4. RESULTS

This work primarily compares the performance of accuracy, precision, sensitivity, F1-Score, latency, and computational efficiency of two existing models and the proposed AGFiLoc model, which are used to adaptively determine the presence and position of a UE in an indoor environment. On this premise, a system of 10 Wi-Fi APs are setup within different floors of the building, while the data collection servers running custom Python scripts for data logging and analysis tools utilize “scikit-learn” for model training and validation. The output of this comparison are delineated in Figure 1 to 5.

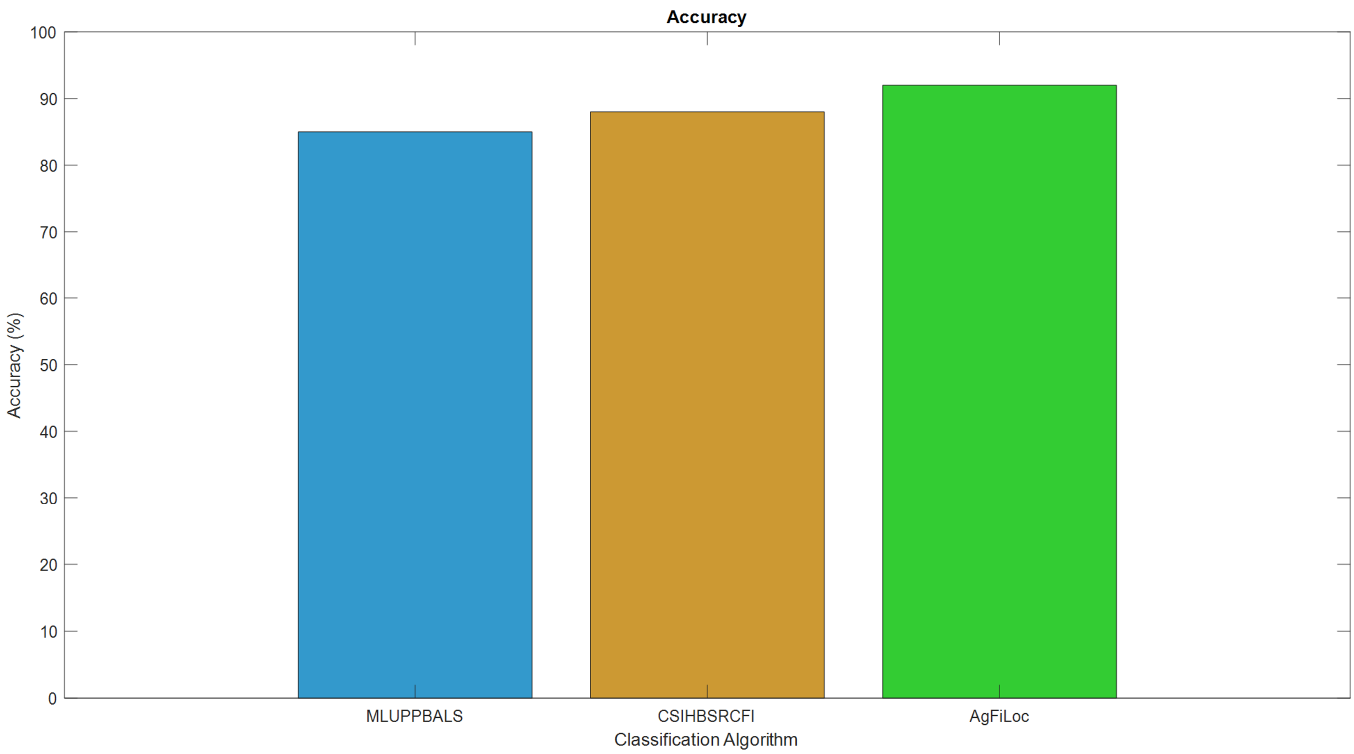

Figure 1. Accuracy Comparison for MLUPPBALS, CSIHBSRCFI and AGFiLoc Algorithms.

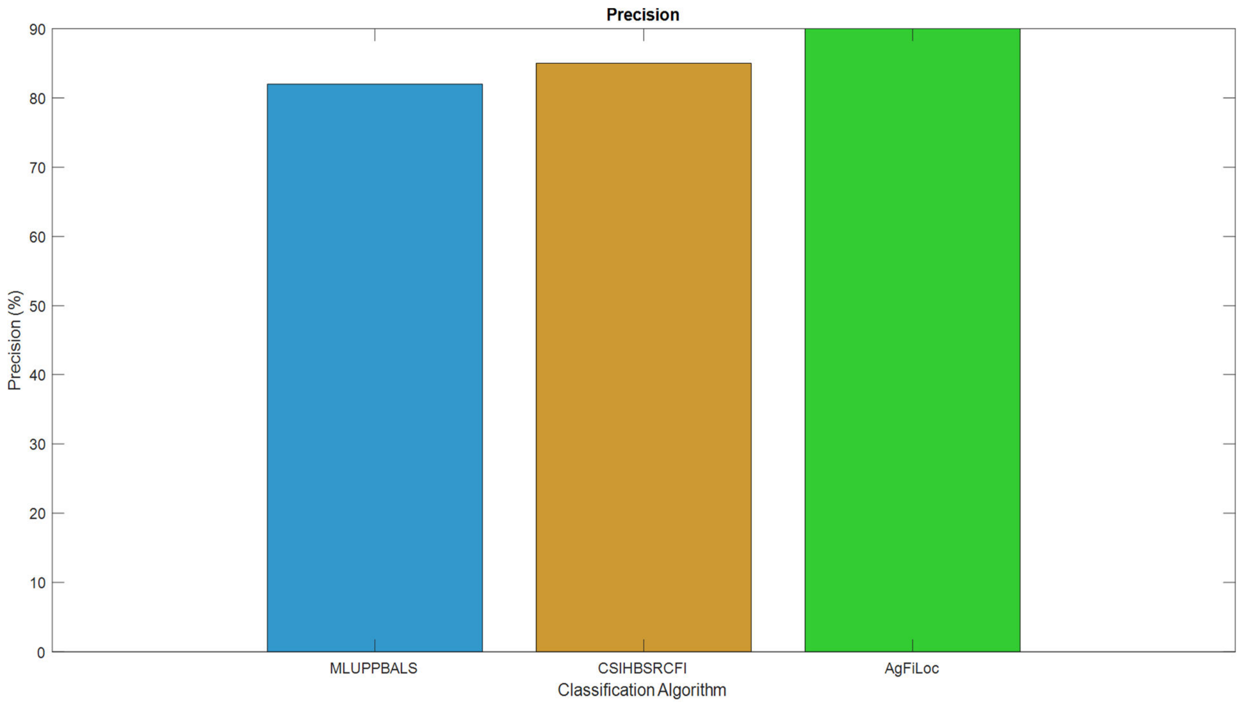

Figure 2. Precision Comparison for MLUPPBALS, CSIHBSRCFI and AGFiLoc Algorithms.

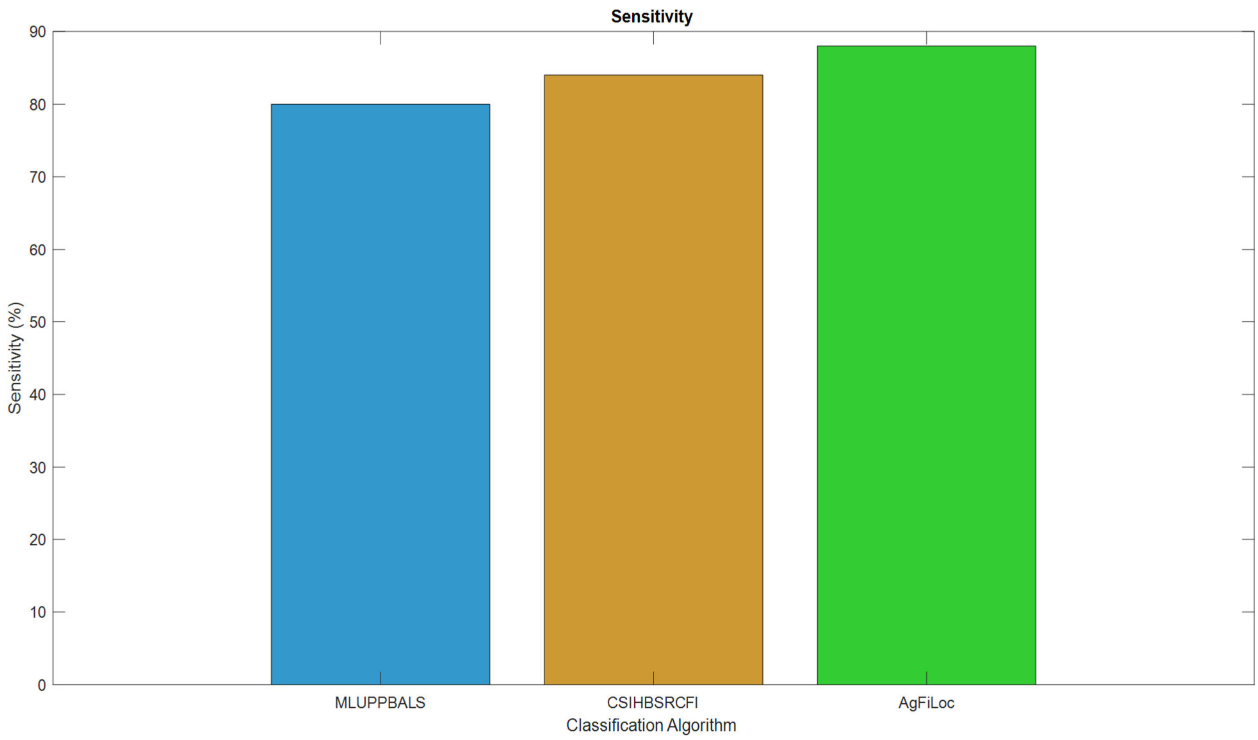

Figure 3. Sensitivity Comparison for MLUPPBALS, CSIHBSRCFI and AGFiLoc Algorithms.

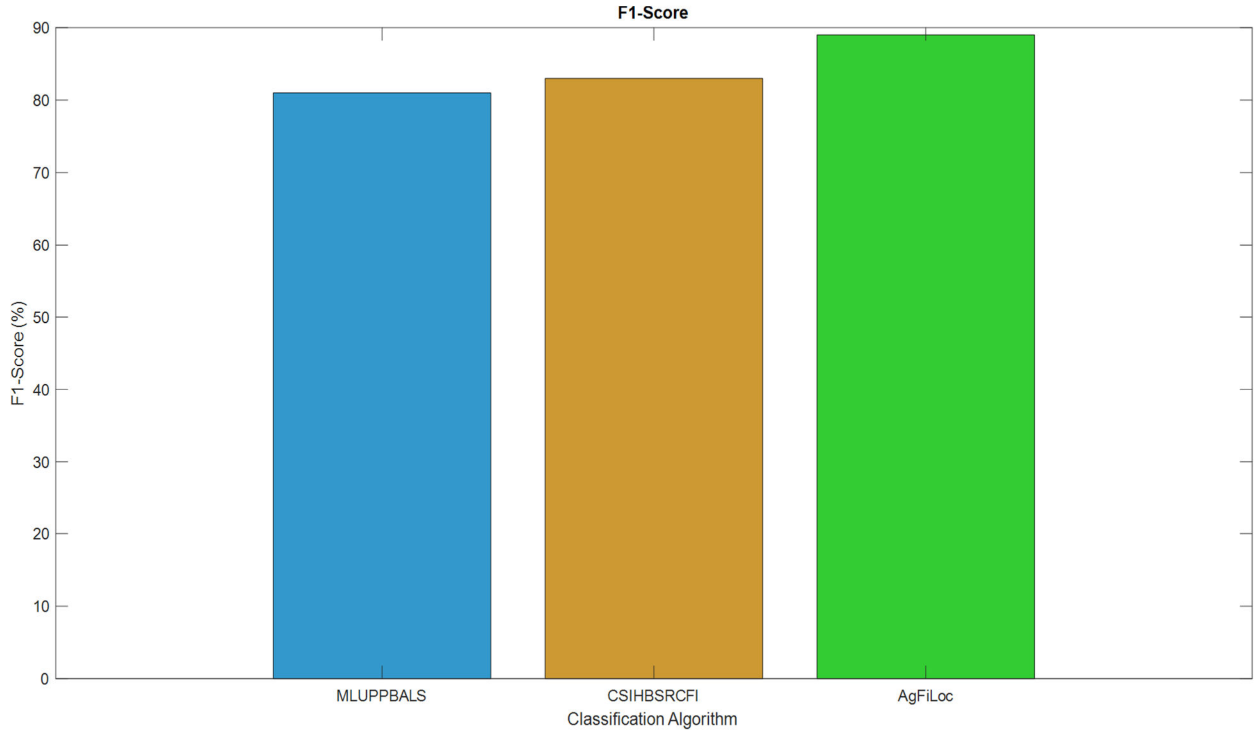

Figure 4. F1-Score Comparison for MLUPPBALS, CSIHBSRCFI and AGFiLoc Algorithms.

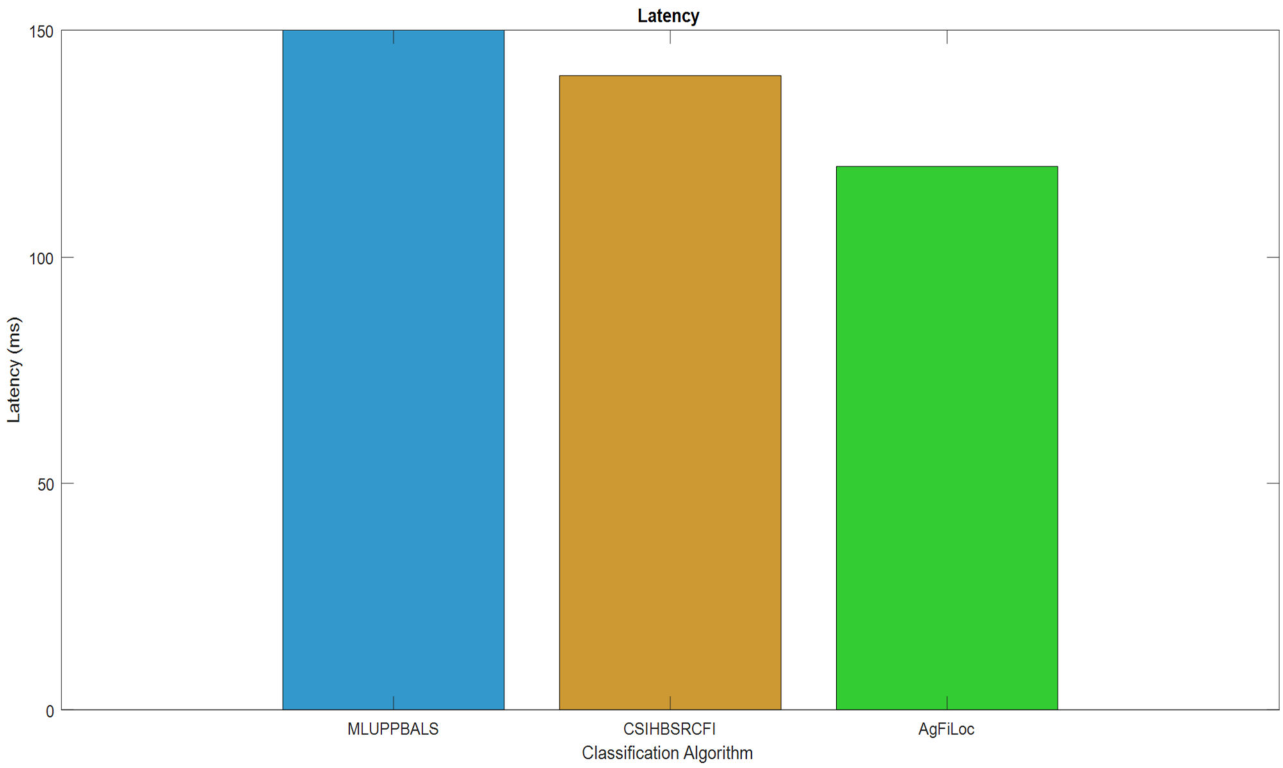

Figure 5. Latency Comparison for MLUPPBALS, CSIHBSRCFI and AGFiLoc Algorithms.

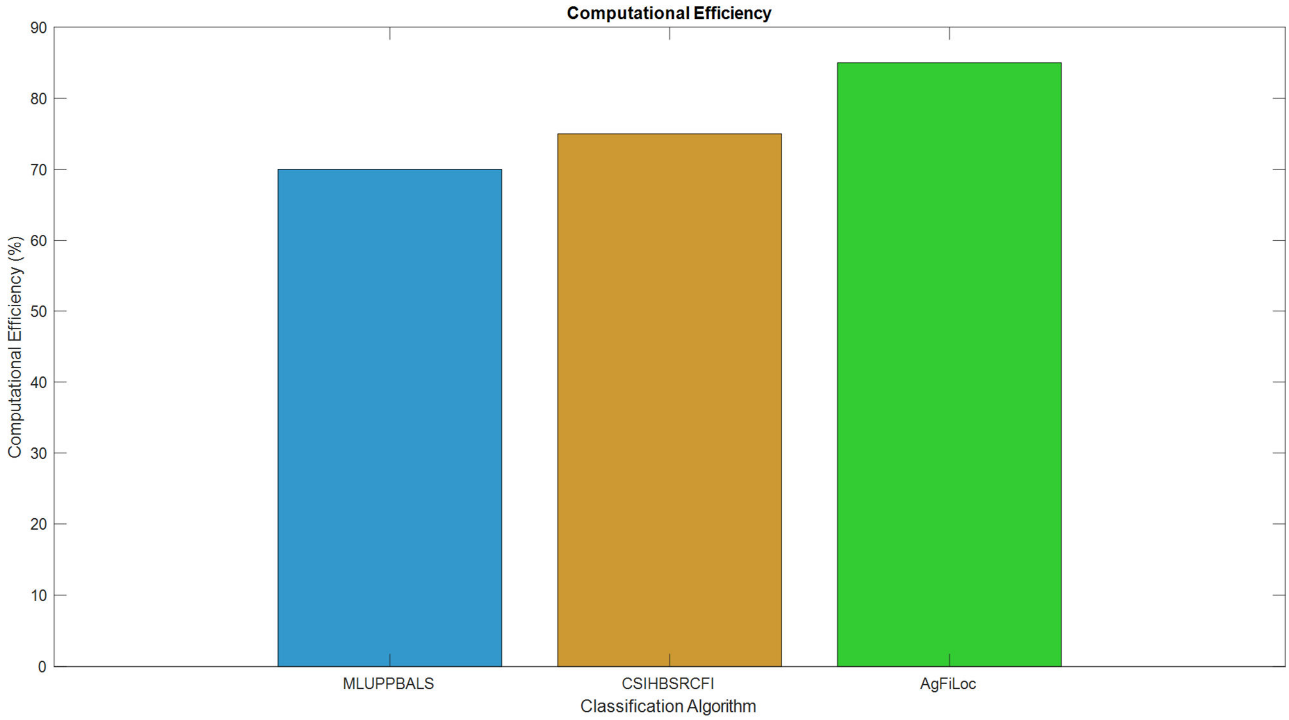

Figure 6. Computational Efficiency Comparison for MLUPPBALS, CSIHBSRCFI and AGFiLoc Algorithms.

Table 1. Performance Improvement.

Performance Metric	**Performance Improvement**				
	MLUPPBALS	**CSIHBSRCFI**	**AGFiLoc**	**Improvement over MLUPPBALS**	**Improvement over CSIHBSRCFI**
Accuracy	85	88	92	8.24	4.55
Precision	82	85	90	9.76	5.88
Sensitivity	80	84	88	10	4.76
F1-Score	81	83	89	9.88	7.23
Latency	150	140	120	20	14.29
Computational Efficiency	70	75	85	21.43	13.33

5. DISCUSSION

The comparison of the proposed AGFiLoc model against the Machine Learning-based User Position Prediction and Behaviour Analysis for Location Services (MLUPPBALS) and CSI-based Human Behaviour Segmentation and Recognition using Commodity Wi-Fi (CSIHBSRCFI) shows that the proposed model outperformed the existing model across the six metrics considered for performance in this paper. The proposed AGFiLoc algorithm outperformed the existing MLUPPBALS and CSIHBSRCFI models in accuracy by 8.24% and 4.55%, respectively. The improvements show that the proposed models ability to better identify and localize the presence of a user. In terms of precision and sensitivity, the proposed AGFiLoc algorithm outperformed the existing MLUPPBALS for precision by 9.76%, and the AGFiLoc algorithm outperformed the MLUPPBALS model for sensitivity by 10%. Against the CSIHBSRCFI Model, the AGFiLoc model showed a percentage improvement for precision and sensitivity by 5.88% and 4.76%, respectively. This represents the proposed AGFiLoc's model capacity to mitigate false positive rates, and improve the capability of true positive detection. The balanced performance of the precision and sensitivity of the AGFiLoc model is represented by the F1-score with percentage improvements of 9.88% and 7.23% against the MLUPPBALS and CSIHBSRCFI models, respectively. The AGFiLoc model achieved significant mitigation in latency against the existing MLUPPBALS model and CSIHBSRCFI model by 20% and 14.29%, respectively. The improvements shows the proposed AGFiLoc model to proficiently process data at a faster rate which is important for user presence detection and handling as well as data privacy in real-time. Finally, the computational efficiency of the AGFiLoc model outperformed the MLUPPBALS model and CSIHBSRCFI model by 21.43% and 13.33%, respectively. As such, the resources used and processed are better optimized in comparison to the existing models.

6. CONCLUSIONS

Adaptively identifying the presence or absence of a user in Wi-Fi-based system is crucial in occupancy characterization. The dynamic nature of UEs can significantly impact the results, as false positives and false negatives can become outliers that can compromise the localization of a UE in the system. To address the aforementioned problem, this work proposes an AGFiLoc model which leverages RSSI to enhance presence detection and movement pattern recognition of UEs in a Wi-Fi system. Sliding window analysis is adopted for user presence detection to better adapt the model to indoor environments. The performance of the proposed AGFiLoc model is primarily compared against two existing models, that is, MLUPPBALS model and CSIHBSRCFI models, while considering accuracy, precision, sensitivity, F1-score, latency, and computational efficiency as performance metrics. The AGFiLoc model outperformed the MLUPPBALS model and CSIHBSRCFI model in terms of accuracy by 8.24% and 4.55%, respectively. In terms of precision and sensitivity, the AGFiLoc model respectively showed a 9.79% and 10% improvement against the MLUPPBALS model, and it respectively showed a 5.88% and 4.76% percentage improvement against the CSIHBSRCFI model. In terms of F1-score, the proposed model outperformed the MLUPPBALS and CSIHBSRCFI models by 9.88% and 7.23%. Additionally, the AGFiLoc model achieved significant mitigation in latency against the existing MLUPPBALS model and CSIHBSRCFI model by 20% and 14.29%, respectively

Furthermore, the computational efficiency of the AGFiLoc model outperformed the MLUPPBALS model and CSIHBSRCFI model by 21.43% and 13.33%, respectively. The margins of improvement of the AGFiLoc model across all performance metrics shows its effectiveness in user presence detection and movement pattern recognition, which are crucial for localization of UEs in the system. Future works would explore the application of the model in other environmental scenarios.

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