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***Abstract*—Accurately classifying regions based on Wi-Fi signals can be a difficult task, especially when considering different frequency values. In this study, we aimed to improve the accuracy of indoor localization by developing a novel approach that does not rely on pre-trained models. To achieve this, fingerprints from the IEEE 802.11az standard were randomly selected, and the data samples were trained using parameterized station characteristics and neural network hyperparameters. The impact of each parameter on the localization accuracy was measured, and performance monitoring metrics such as F1-Measure and confusion matrix-based metrics were evaluated. Furthermore, the Thompson sampling (TS) algorithm was employed to determine the optimal parameters, which helped to achieve the best possible accuracy. The proposed approach demonstrated improved accuracy in region localization compared to conventional heuristic approaches which typically yield an accuracy range of 65% to 77%. The proposed approach achieved up to 80% accuracy in region localization and could be a promising solution for indoor localization in various settings.**

***Keywords*—Convolutional neural network (CNN), IEEE 802.11az Wi-Fi standard, optimization, Thompson sampling (TS).**

I. Introduction

The increasing presence of smart sensors in various locations has created a demand for accurate and reliable localization of specific devices in Internet of Things (IoT) applications. This need is particularly evident in settings such as hospitals, where the ability to locate medical staff, equipment, and patients would significantly improve the quality and efficiency of medical services. Achieving precise localization in both indoor and outdoor environments, while minimizing power consumption, is crucial [1]. While the global positioning system (GPS) has been commonly used for localization, its effectiveness indoors is limited by non-line-of-sight (NLOS) challenges. As a result, various technologies have been proposed to enable indoor localization, including magnetic field-based methods [2], Bluetooth [3], WiFi [4], Ultra Wide Band (UWB) [5], and RFID [6], among others. WiFi, in particular, offers high availability and accuracy, although it comes with slightly higher power consumption. This characteristic enables widespread and accurate localization in nearly any environment with compatible devices.

The next generation of WiFi positioning, known as next-generation positioning (NGP), relies on the IEEE 802.11az Wi-Fi™ standard [7] and utilizes Time-of-Flight (ToF) measurements to facilitate location-based services. In this context, localization refers to the ability to determine the position of a wireless device, such as a smartphone or laptop, within a given environment. The IEEE 802.11az standard employs ToF measurements to calculate the distance between a wireless device and multiple access points (APs) in the environment. These measurements are based on the time taken by a signal to travel from the device to the AP and back. By leveraging multiple APs and triangulation, the location of the device can be accurately determined.

Traditional methods rely on direct line-of-sight (LOS) conditions to extract sequential data, such as angle of arrival (AoA), spatial information, or time of arrival (ToA), from signals that encounter multiple paths. This extraction enables the calculation of distances or ranges between network nodes. Trilateration, a technique that estimates positions by measuring the range among three devices, becomes viable once this range can be measured. To achieve precise localization in WiFi networks, deep learning, and fingerprinting systems are employed, enabling sub-meter accuracy even in environments with multipath signals where direct line of sight is not available.

In the scenario presented in this study, multiple access points transmit 802.11az packets through a channel affected by noise. By utilizing the NGP techniques, it is possible to optimize the accuracy of indoor localization in this scenario. Each station receives the packets, and it is assumed that the stations are capable of distinguishing between the different access points; there is no interference between the access points. The experiments include four access points, as shown in

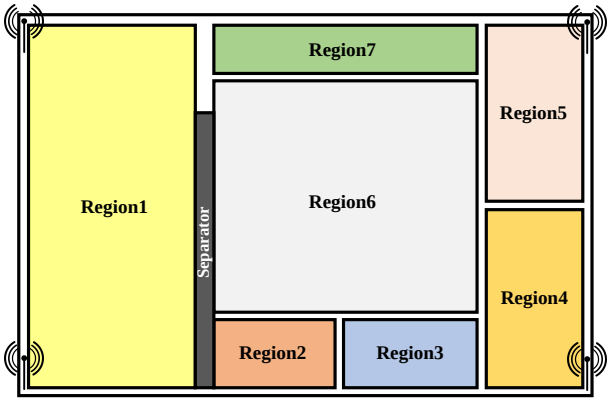

Figure 1: The scenario (5 m × 8 m × 3 m) under consideration consists of classification regions encompassed by access points [7], [11].

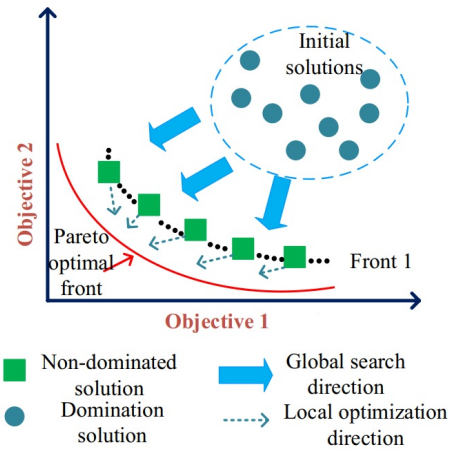

Figure 2: A general view on the Pareto front in two-objective optimization [16].

Fig. 1. The number of stations for fingerprinting is a parameter. Uniform or random placement is possible; this work assumes the 3-dimensional random positioning. The fingerprints for each access point are generated based on the characteristics of the propagation channel [8], [9], and ray tracing techniques [10] are used to generate the corresponding channel impulse response (CIR), which can effectively capture the effects of reflections, diffractions, and scattering on the CIR. In recent years, researchers have investigated the application of ray tracing techniques in generating CIRs for different wireless communication systems, including Wi-Fi, 5G, and IoT.

The rest of the paper is organized as follows: Section II presents the proposed method based on training a neural network (NN) with hyperparameter and Wi-Fi set-up optimizations. Section III devotes to presenting the simulation results, and Section IV concludes the paper.

II. Parameter Optimization with CNN

Constructing a NN involves two steps: (i) deciding on the NNs' structure and (ii) achieving optimal hyperparameters, such as the number of neurons, hidden layers, dropout size, training-validation ratio, batch size, and more. This section will provide a general description of constructing a convolutional neural network (CNN) using a proposed method to obtain the optimal hyperparameters for indoor localization with the help of Wi-Fi signals.

A. CNN Construction

A CNN is a structure used in deep learning systems to extract features without the need for human intervention automatically. The obtained features are used to train a system and classify test data using the resulting model. In this study, a database is created during the network's training phase by sampling channel fingerprints at various known locations in an indoor environment. The network estimates the user's location based on a signal received at an unknown location by referencing the database. The hyperparameters of the CNN and Wi-Fi signaling parameters are used during optimization.

The CNN structure includes four network layers: convolutional, batch normalization, ReLu (rectified linear unit), and average pooling. Fully connected layers that process data finalize the network including a grid-like construction [12], and the convolution layer is the main module for getting features automatically. The pooling decreases the number of computations where the fully connected layer is attached to the previously described layers. This network is selected over the various networks to handle a variety of computer vision problems [13] and estimate the exact position of multiple stations based on the fingerprints and the position labels.

Our observations for the CNN structure are to keep the convolution+batch+relu+pooling (`connected layer group – CLG`) together in a cascading fashion. Each connected layer group increased from 1 to 5 to measure the performance during the training. This is one of the objectives the TS algorithm considers. Each `CLG` is identical and convolutions have 256 filters with 3-to-3 sizes [11]. Average pooling follows the down-sampling by a factor of two.

B. Hyperparameter Optimization through TS Method

For any NN, suitable hyperparameters lead to constructing an accurate network are required importantly. For this case, obtaining optimal hyperparameters is not straightforward and requires efficient optimization methods. The TS algorithm is based on the Bayesian optimization (BO) method that builds the Gaussian process (GP) [14]. This method targets to find the proper global minimizer x^* of a function $y(x^* \in argmin_{x\epsilon\chi\subseteq\mathbb{R}^d} y(x))$. In total, this method approximates the Pareto front where the final output data is the set of points nearby the precise Pareto set [15]. The general idea of the Pareto front is presented in Fig. 2.

In this study, the CNN is trained where the TS method is employed for optimizing parameters such as the transmit and receive antennas (TA and RA), the number of fingerprints (NoF), the training-validation data split ratio (SR), and the CNN parameters such as `CLG` counts, activations, dropout (DO), and batch size (BS). Another objective of the TS method is the validation of the confusion matrix characteristics and determining the best-performing network structure by considering both accuracy and performance monitoring metrics such as sensitivity, precision, specificity, F1-Measure, balanced accuracy, and Fowlkes Mallows Index (FMI). The confusion

Table I: Performance Monitoring Equations [17]

Sensitivity	$\frac{TP}{(TP+FN)}$	**F1-Measure**	$\frac{2\times TP}{2\times TP+FP+FN}$
Precision	$\frac{TP}{TP+FP}$	**Balanced Acc.**	$\frac{Sensit.+Specif.}{2}$
Specificity	$\frac{TN}{(FP+TN)}$	**FMI**	$\sqrt{(Prec. \times Sensit.)}$

matrix for the seven regions (in Fig. 1) shows the multi-class classification results using TP: True Positives, FP: False Positives, TN: True Negatives, and FN: False Negatives. The performance monitoring formulas are represented in Table I.

III. Simulation Results

This work presents classification results of an indoor area, which is divided into a total of seven zones. The testing workspace consists of four sites with 802.11az access points that send and receive signals. We optimize several parameters, including the TA, RA, NoF, SR, and CNN parameters, such as `CLG` counts, DO, and BS. TA, RA, and NoF are Wi-Fi set-up-related parameters to be optimized. SR, `CLG`, DO, and BS are the neural network-related hyperparameters. For data acquisition, using a MATLAB simulator [11], we use an iterative data generation that assumes random positions of stations. The summary of the parameters is presented in Table II. Here, we provide a summary of the ranges (initial value: step size: final value) for the optimization parameters of the Wi-Fi network and the NN, as well as their best-performing values (indicated in **bold**).

In the experiments, the fingerprints are obtained and then split into training, validation, and testing points. During iterative training, we change the hyperparameters, and we record single-step changes in each parameter, such as updating the batch size from 16 to 32, while considering the validation accuracy and confusion matrix. The optimal confusion matrix metrics in the validation check sets the reference Pareto optimal fronts to fine-tune the optimization. Each selected metric has been chosen for a specific observation. Specificity, also known as the True Negative Rate or inverse sensitivity, represents the proportion of correctly identified negative cases. Sensitivity, also known as recall or the True Positive Rate, measures the correctly predicted positive values. Precision, or the Positive Predictive Value, monitors the measure of actual positive cases. Powers refer to precision as the True Positive Accuracy, indicating the confidence score [18]. From sensitivity and precision, the F1-measure is calculated using the harmonic mean or the indicated formula in [17]. To provide a better perspective for performance analysis, balanced accuracy considers an imbalanced confusion matrix, and it is the arithmetic mean of sensitivity and specificity. FMI stands for a clustering performance measure, assuming that the classification is similar to data clustering [17].

In Fig. 3, we present the testing results obtained after optimizing the model through validation. Our observations indicate that better results were obtained when the numbers of TA and RA were both set to four and increasing the number of NoF did not guarantee an increase in accuracy. Therefore, obtaining a large amount of fingerprint data may not necessarily ensure higher accuracy. This localization problem has become more challenging, highlighting the importance of optimization. The reported 68.40% classification accuracy in the literature [19] has been improved to 80.01% in this study.

Table II: Summary of Simulation Parameters Including NN

Parameters	Values
Number of the zones	7
Dimensions of the indoor location	5 m × 8 m × 3 m
Number of access points	4
Counts of TA and RA	1, 2, or **4**
Wi-Fi Channel Width	20, 40, 80, or **160** MHz
NoF range	500:10:1000 (**750**)
Hyperparameters of CNN CLG range	1:1:5 (**4**)
SR range	5:5:25 (**15**%)
DO range	5:5:35 (**10**%)
BS range	16:8:256 (**16**)

The decreasing color contrast in the metric group presented in Fig. 3 matrix format can be observed after optimization. Additionally, with Wi-Fi access points in every corner of a closed environment, we observed that classifying the edge regions was more challenging compared to the central regions.

IV. Conclusion

Constructing a convolutional neural network involves deciding on its structure and achieving optimal hyperparameters. In this study, a CNN was constructed to estimate the user's indoor location using Wi-Fi signals. The CNN structure includes convolutional, batch normalization, ReLU, and average pooling layers, with fully connected layers finalizing the network. The hyperparameters were optimized using the Thompson sampling algorithm based on Bayesian optimization. The TS algorithm optimized the parameters in terms of transmit and receive antennas, the number of fingerprints, the training-validation data split ratio, and the CNN parameters. The TS algorithm also considered accuracy and performance monitoring metrics such as sensitivity, precision, specificity, F1-Measure, balanced accuracy, and Fowlkes Mallows Index to determine the best-performing network structure. The results showed that the proposed method achieved high accuracy in estimating the user's location in different regions of the indoor environment. This study has tackled a more challenging task by overcoming limited training data without utilizing pre-trained data, which opens up possibilities for future work to incorporate pre-trained network models.

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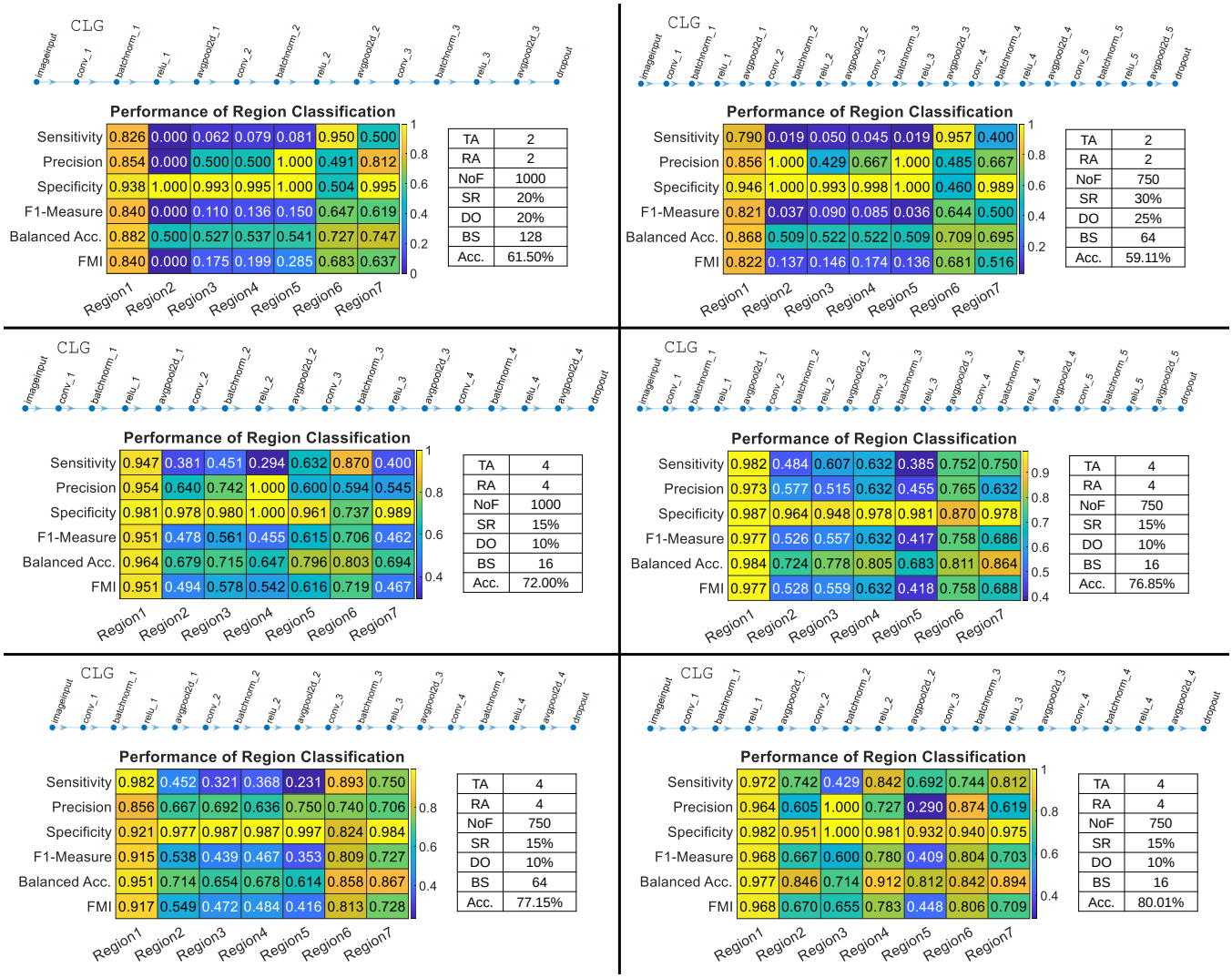

Figure 3: Classification accuracy results and different performance monitoring metrics for region localization. From the left-top to the right-bottom TS method optimizes the parameters in each sub-table and the CLG.

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