Indoor Localization of Industrial IoT Devices and Applications Based on Recurrent Neural Networks

Ivan Marasović, Goran Majić, Ivan Škalic, and Željka Tomasović

***Abstract*—Industrial Internet of Things (IIoT) has become an indispensable element of smart industrial facilities, predicted to continue to grow at a rapid rate. Wireless technologies have become a standard part of today's industrial facilities with applications including programming and control of electric drives, remote system and environment monitoring and fault diagnostics of industrial equipment. However, installation of physical connections can be time consuming and require substantial economic resources, especially when considering long-term maintenance costs. With that regard, IoT applications that use sensor technology, RFID technology, network communication, data mining and machine learning could prove to be quite efficient in solving the previously presented problem of localization. A new indoor localization algorithm has been introduced based on recurring neural networks (RNNs) for the positioning of indoor devices. Experiments were conducted in relatively complex surroundings of a faculty building. According to experimental results, the presented system surpasses the state-of-the-art algorithms and can achieve 98.6% localization accuracy of indoor devices.**

***Index Terms*—Wi-Fi, Signal Strength, Localization, IIoT.**

I. Introduction

The emergence of the Industrial Internet of Things (IIoT) has been pivotal in the transformation of smart industrial facilities into highly integrated and efficient systems, and its influence is expected to escalate further. This paradigm encapsulates the widespread deployment of technologies such as sensors and actuators, which are interconnected through the advancement of wireless communication methods, marking a significant shift in industrial operations [1]. The integration of wireless technologies has become a fundamental aspect of modern industrial settings, facilitating a broad spectrum of applications from the programming and control of electric drives to the remote monitoring and diagnostics of systems and machinery. The adoption of wireless infrastructure in industrial contexts enables the seamless interconnectivity of various devices, eliminating the need for physical wiring [2]. The process of establishing wired connections, in addition to being labor intensive, also incurs considerable financial outlays, particularly when factoring in maintenance expenses over time [3]. Additionally, physical cables are susceptible to damage under the mechanical and electrical stresses prevalent in the strenuous conditions of industrial environments. Despite the primary objective of bypassing the need for direct device connections, wireless technology offers additional benefits, such as the ability to locate and track components within industrial premises [4, 5]. Parallel to the ubiquitous nature of personal devices like smartphones, which incessantly gather data from their vicinity, the complexity and quantity of devices within IIoT networks, alongside the volume of data they amass, are on an upward trajectory [6, 7]. Consequently, it is imperative for IIoT systems to adeptly manage data acquisition, facilitate machine-to-machine communications, and, if necessary, preprocess the collected data, all while balancing between cost, computational efficiency, and energy consumption [8]. This data serves as a foundation for the development of technologies, for instance, Wi-Fi-based positioning systems, by leveraging the connectivity of devices as beacons [9].

Compared to conventional GPS-based methods, which dominate outdoor localization but struggle with accuracy and reliability indoors due to signal attenuation and multipath interference, Wi-Fi-based localization offers a significant advantage. Unlike GPS, Wi-Fi localization is not impeded by roofs or walls. Instead, it uses existing network infrastructure, making it a more feasible and economical option for comprehensive coverage in complex industrial buildings. Moreover, Wi-Fi-based methods can capitalize on the high density of access points within industrial settings to enhance localization accuracy through techniques like fingerprinting, which maps the unique characteristics of Wi-Fi signals at different locations. Recent studies, such as those conducted by [10] and [11], have explored various aspects of localization technologies in industrial environments, highlighting the importance of accuracy, reliability, and cost-effectiveness. These works underscore the potential and challenges of GPS and other technologies in achieving high localization precision within complex indoor and outdoor transitions. In this context, our Wi-Fi-based localization method addresses these challenges by providing a robust, adaptable, and cost-efficient solution, harnessing the full potential of existing Wi-Fi infrastructure and advanced machine learning techniques to meet the unique demands of industrial localization.

The advancement of wireless indoor positioning technologies, including Wi-Fi, Bluetooth, and ultra-wideband, has led to the creation of numerous systems designed to offer location-based services within large facilities [12]. Among

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these, Bluetooth and Wi-Fi have emerged as prevalent methodologies for signal-based localization. Both technologies exploit characteristics of wireless signals, such as Received Signal Strength Indicators (RSSIs) or Channel State Information (CSI), for the estimation of spatial coordinates. In addition, they incorporate the technique of fingerprinting, establishing a database of signal attributes at various points in advance to facilitate optimal location identification through matching algorithms.

The utility of indoor localization spans several domains, encompassing emergency response, navigational aids, logistical operations, and intelligent residential management. For example, Filippoupolitis et al. [13] have advocated for the use of Bluetooth Low Energy (BLE) to address the challenge of determining occupancy during emergencies, using beacons for spatial information dissemination and integrating machine learning for the assessment of the presence of the inhabitants. In the realm of efficient energy use, Tekler et al. [14] introduced an innovative system to manage electrical loads, merging BLE with algorithmic learning to infer occupancy and thus optimize energy consumption through automated control. Similarly, leveraging existing Wi-Fi networks and mobile devices, Balaji et al. [15] proposed a method for occupancy-driven regulation of heating, ventilation and air conditioning (HVAC) systems in commercial settings. Furthermore, Tekler et al. [16] highlighted the importance of selecting key sensor data characteristics for occupancy prediction using various deep learning models.

The extensive deployment of Wi-Fi on residential and commercial premises makes it a powerful tool for location services [17]. Wi-Fi technology was used to capitalize the ubiquitous nature of mobile devices and the comprehensive signal coverage provided by Wi-Fi networks. Wi-Fi positioning systems, particularly those that use fingerprinting techniques, have gained popularity for their ability to accurately pinpoint indoor locations by analyzing RSSI signals. The RSSI range method, which estimates distances based on signal strength attenuation, is instrumental in this context, obviating the need for additional hardware and thus minimizing implementation costs [18, 19].

H. Lu et al. [20] refined indoor positioning accuracy by integrating a weighted nearest neighbor (WKNN) algorithm and an extreme gradient boosting technique (XGBoost), achieving a notable decrease in localization errors. The articles [21, 22, 23] have employed supervised classifiers for indoor positioning tasks, using machine learning algorithms such as neural networks (NN), feedforward neural networks (FFNN), support vector machines (SVM), and k-Nearest Neighbors (kNN). In [23] it is highlighted that while NNs offer high accuracy, they require considerable computational resources. Furthermore, the introduction of recurrent neural networks (RNN) and long-short-term memory (LSTM) models for device positioning illustrates the potential to achieve high levels of accuracy in determining device locations, even within constrained environments [24].

Building upon these advances, the present research introduces a neural network (NN)-based model for fingerprint indoor localization. In summary, the principal contributions of this paper are as follows:

- *Framework Development for IIoT Indoor Localization:* The paper introduces a novel approach for indoor localization of devices in Industrial Internet of Things (IIoT) settings by leveraging the variability in wireless signal strength. This framework represents a significant advancement in utilizing existing Wi-Fi infrastructure for precise indoor positioning, eliminating the need for additional specialized hardware.
- *Utilization of Neural Networks for Enhanced Accuracy:* By applying neural networks to process RSSI data from Wi-Fi access points, the study showcases how machine learning techniques can be effectively used to improve localization accuracy. The use of neural networks for analyzing signal strength variations marks a pivotal step in the practical application of AI for indoor localization tasks.
- *Achievement of High Localization Accuracy:* The methodology employed in this study is capable of pinpointing device locations with an accuracy of up to 98.6%. This high level of precision in determining device positions within complex indoor environments underscores the effectiveness of the proposed neural network model.
- *Extensive Dataset Collection and Analysis:* With the collection of more than 30,000 data points related to Wi-Fi signal strength measurements, this study lays a strong foundation for future research in signal analysis for localization purposes. The comprehensive dataset supports the validation of the neural network model and highlights the potential for further optimizations and enhancements.

The paper is organized as follows: Section II explores various Wi-Fi localization techniques, focusing on the use of the Received Signal Strength Indicator (RSSI) and advancements in indoor positioning. Section III discusses methods and mathematical methods, as well as the realization of the device, along with preliminary analysis. Section IV delves into the Neural Networks model, and discusses Algorithm Evaluation Techniques, as well as the result of indoor localization. Finally, the Conclusion summarizes the findings on the efficacy of neural network approaches in indoor device localization and outlines future research directions.

II. Related Work

Innovations in improving indoor Wi-Fi positioning include the adoption of the local principal gradient direction, as described in [25]. Here, the creation of a calibration device mesh, each designated with a specific principal gradient direction, facilitates the identification of proximal calibration points through distance correlation. The position estimation is then refined using the weighted squared Euclidean distance to the nearest calibration point. Another significant advancement is the application of Recurrent Neural Networks (RNN) and Long Short Term Memory (LSMT) models for device positioning, demonstrating high precision in floor-level prediction with minimal distance errors ranging from 2.5 to 2.7m [24]. The study reveals that adding complexity to the RNN and LSTM frameworks yields marginal benefits relative to the increased demands on training and testing durations.

Further research has explored pre-training systems with RSSI data to enable real-time positioning [26], and the use of deep learning techniques to infer human movement from Wi-Fi channel state information [27]. Integrating additional data types has been shown to enhance indoor positioning accuracy. A notable investigation by [28] combined barometer readings with information from five Access Points to achieve three-dimensional user localization with less than 1.2 m error margin, conducted at the University of Genoa and the University of Bologna. This study introduced a novel 3D indoor localization algorithm and found that incorporating barometer data improved positioning success by up to 22% when using more than five Access Points. This body of work underscores the evolving landscape of indoor positioning technology, highlighting the potential of integrating diverse data sources and advanced computational models to refine accuracy and reliability.

In a study by Aigerim et al., an ML classifier-based methodology was used for indoor localization purposes [29]. This investigation leveraged RSSI data collected from Sony Xperia XA1 mobile devices and BLE product iTAG signal emissions, pinpointing the iTAG position at a building entrance. Dataset collection was facilitated by students, with three groups, each comprising 12 students, assigned an iTAG device. These groups navigated a confined area with their activated iTAGs, covering three designated spots at the entrance of the building, including inside, in the vestibule, and outside, along an 18.35 m × 3 m hallway. Signal capture was executed using two Sony Xperia XA1 smartphones positioned at both ends of a 2.35-m "in vestibule" segment, over a 20-minute duration. The dataset comprised raw and filtered RSSI readings, with raw RSSIs obtained directly from smartphones and filtered RSSIs processed through a feedback filter. Training on these datasets with Naive Bayes and Support Vector Machine algorithms yielded a 0.95 accuracy rate for SVM with four vectors.

Singh and colleagues made significant contributions to the field by exploring indoor location based on mobile phones through ML methodologies. Their experimental setup involved the collection of 3110 RSSI data points within an indoor testbed and the evaluation of various machine learning algorithms, including kNN, RFR, Multilayer Perceptron, and ZeroR. Their findings demonstrated that the proposed ML techniques outperformed traditional indoor localization methods, achieving a mean error of approximately 0.76 m. They also proposed a novel hybrid instance-based approach that significantly improved performance by tenfold without compromising accuracy. The study highlighted the precision of the proposed methods, their applicability in practical scenarios, and their robustness against sparse datasets, particularly demonstrated through an online, in-motion experiment, validating these methods' suitability for real-world applications [30].

Kaur and her team conducted research on RSSI- and ML-based indoor localization strategies, utilizing Neural Networks for localization based on RSSI measurements. The study compared position estimation results using Artificial Neural Networks (ANN) and Decision Trees, employing an ANN with three inputs for initial position estimates of RSSI triplets and later with four inputs for enhanced precision. This comparative analysis revealed superior accuracy of the algorithms tested over the decision tree approach [36].

Jun et al. introduced an approach that enhances RSSI-based localization accuracy through weighted least-squares techniques. By adopting weighted multilateration, this method aimed to mitigate error susceptibility and reduce the reliance on ideal channel models. Using weighted least squares techniques adapted from traditional hyperbolic and circular positioning algorithms, the study achieved enhanced localization accuracy with minimal additional computational overhead, validated through extensive real-world testing in various wireless networks and numerical simulations [31].

Ashraf et al. [32] present a significant contribution to the field of indoor localization by introducing a deep neural network (DNN)-based approach that leverages magnetic field data for positioning. This approach stands out by utilizing a soft voting mechanism to ensemble predictions from multiple DNNs, all trained on the same magnetic data, to enhance localization accuracy.

Maduranga et al. [23] present a novel method for indoor localization using Bluetooth Low Energy (BLE) and Feed Forward Neural Network (FFNN), aimed at enhancing location-based services in IoT applications. By training on RSSI values from thirteen different BLE iBeacon nodes, the study successfully demonstrates the feasibility of using FFNN to accurately classify the location of an object within an indoor environment.

Che et al. [33] introduce a machine learning-based approach for indoor localization using ultra wide bandwidth (UWB) systems, aimed at improving accuracy in Industrial Internet of Things (IIoT) applications. By developing and employing a Naive Bayes machine learning algorithm, the research addresses the challenges of line-of-sight (LoS) and nonline-of-sight (NLoS) conditions in UWB indoor localization.

Koutris et al. [34] introduce a novel deep learning-based method for indoor localization using low energy Bluetooth (BLE) signals, leveraging multiple anchor points for the estimation of the angle of arrival (AoA). This approach, for the first time, utilizes both raw IQ values and RSSI estimates for ML-powered BLE-based positioning, proposing a range of novel deep learning architectures.

The research paper in [35] investigates the impact of using dual-frequency SSIDs from Wi-Fi Access Points on indoor localization accuracy using machine learning regression algorithms. The findings indicate that dual-frequency SSIDs significantly improve location prediction accuracy, and the Support Vector Regression (SVR) algorithm outperforms other classical machine learning methods.

Xudong and colleagues proposed CNNLoc [37], a deep learning-based indoor localization system for multi-floor environments, utilizing a novel model that combines a one-dimensional Convolutional Neural Network (CNN) with a stack autoencoder (SAE). This system, designed to achieve high accuracy in building and floor level localization, demonstrated superior performance over existing methods on the

TABLE I
COMPARISON OF DIFFERENT MACHINE LEARNING ALGORITHMS FOR LOCALIZATION.

Reference	*ML Algorithms Used*	*Remarks*	*Used hardware*
[31]	Convolutional Neural Networks	Good accuracy	n/a
[32]	Neural Networks	77% accuracy	Samsung Galaxy S8
[23]	Neural Networks	78% accuracy	Gimbal Beacons
[33]	Support Vector Machine	82% accuracy, Wi-Fi used	n/a
[34]	Decision Tree-Based Localization	Decent accuracy of DT	receiver with an L-shaped antenna array
[35]	Self-Organizing Map	Fairly good accuracy provided. Wi-Fi was used	Raspberry Pi 4B and an iPad
[30]	Neural Networks	Low accuracy	Estimote
Our method	Neural Networks	High accuracy 98,6% Wi-Fi was used	ESP32

UJIIndoorLoc and Tampere datasets, showing success rates for building and floor-level localization. Table I shows the comparison study of the existing work and the results.

III. METHODS AND MATERIALS

Location fingerprinting serves as a sophisticated technique for inferring geographical locations by capitalizing on unique characteristics associated with particular environments [38]. In this approach, a "fingerprint" is defined as a combination of distinct attributes or indicators that identify a geographical area. Specifically, in the context of Wi-Fi research, a fingerprint includes a collection of Received Signal Strength Indicators (RSSIs) collected from a variety of Access Points (APs) at a specific site. The methodology underlying location fingerprinting divides into two essential phases: the offline phase and the online phase. The offline phase is characterized by the collection of features from several sites within a test environment to create a reference database or mapping. This reference collection contains a variety of fingerprints, each linked to their respective geographical coordinates. In contrast, the online phase involves collecting features from an unknown location to determine its location based on its fingerprint. This fingerprint is then cross-referenced with the database entries to determine the geographical position of the unknown site. A schematic representation of the proposed system architecture is provided in Figure 1, which offers a visual overview of the operational framework. Therefore, as described in detail in Section IV the input for the neural network (NN) model is established as $RSSI_{i,k} = (x_{i1}, ..., x_{ij}, ...x_{in})$, where $RSSI_{i,k}$ constitutes a one-dimensional vector that encompasses the extent of k RSSI measurements from the wireless access points at position i, where j determines the RSSI of jth access point, determined with a unique SSID and a MAC address. Throughout the training stage, each RSSI measurement is matched with a distinct label indicative of locations in different rooms. For example, the expression $(RSSI_{i,k}, i)$ illustrates the RSSI fingerprint $RSSI_{i,k}$ linked to the ith specific location of the building. The data collected are passed to a centralized database with high computational power to train a deep neural network model. To facilitate the training process, the data set is divided into three segments: the training set, the validation set, and the test set. Upon training, the test set data is validated on a model to estimate the location of a device.

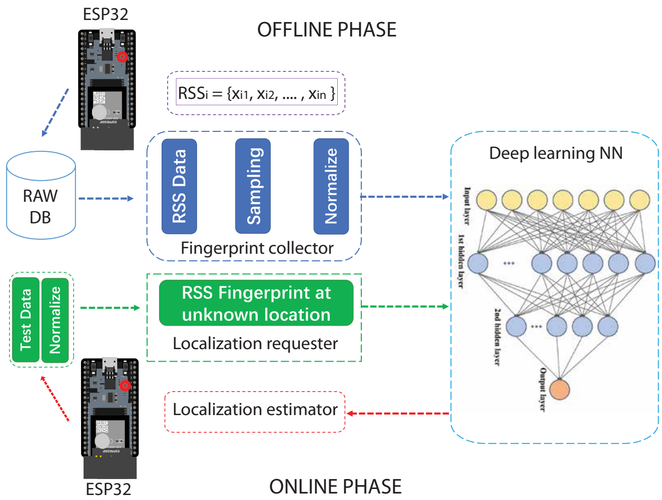

Fig. 1. System Architecture

A. Experimental Setup

At the heart of the sensor apparatus lies the Espressif Systems ESP32 microcontroller, which is equipped with integrated Wi-Fi and Bluetooth capabilities, as shown in Figure 1. In the first phase, ESP32 enters the scan mode, where it captures data related to SSID, MAC address, and RSSI of neighboring access points. After that, the collected data is passed over Wi-Fi to a centralized database using the MQTT protocol for further analysis. Illustrated in Figure 2 are the various sites within a university building where ESP32 devices were installed (pisiotions 1-24) to collect data on the strength of the Wi-Fi signal from neighboring access points, comprising a total of 24 different locations where these ESP32 devices were deployed. These devices were strategically placed in four rooms located on the same floor, and two of the rooms were located within the same building sector. The objective behind this indoor localization effort was to evaluate the capability of the designated machine learning model to accurately identify the device's specific location, whether it be within a particular room or a broader building sector. In total, this study collected more than 30,000 data points related to measurements of the strength of the Wi-Fi signal.

The experimental setup for the machine learning tests was configured with a hardware and software environment that included an Intel Core i7-7700HQ CPU operating at 2.80 GHz,

Fig. 2. Measurement locations.

16 GB of system memory, an NVIDIA GeForce GTX 1050 for graphics processing, and ran on a 64-bit version of Windows 10. To enhance the performance on the GPU, the NVIDIA CUDA toolkit (cuDNN) was employed. For conducting the experiments, which varied in batch sizes, the Keras library version 2.3.1 was utilized, which relies on Tensorflow 2.2.0 and supports CUDA for GPU acceleration.

B. Wi-Fi Data Analyses

The examination of Wi-Fi data necessitated a distinctive analytical approach, given the presence of 397 access points (APs) and in excess of 30,000 received signal strength indicators (RSSI). For a complete comparative analysis, specific attention was redirected toward the data emanating from rooms A242 and 243 in Figure 2, with a more detailed analysis provided. Regarding the location pairs discussed above, their respective RSSI readings were revisited (vectors $RSSI_{i,k}$ at locations $i = \{A242, A243\}$. Figure 3 shows a histogram of RSSI values collected at location points 4 and 12 in rooms A242 and A243 from a specific access point (AP 2 in this example). As can be seen, there is some degree of overlap for locations within different rooms, although with a clear distinction; for example, lower RSSI readings were typically associated with location 4, while higher values were more common for location 12, when considering the same AP. This differentiation hints at the nuanced spatial distribution of signal strengths across different locations, offering a valuable perspective for interpreting Wi-Fi data in spatial analyses.

This clearly indicates that Wi-Fi data can indeed represent a source of localization information, especially in dense industrial environments with multiple access points deployed in numerous locations. Moreover, combining such data on signal strength with an appropriate deep learning algorithm from multiple access points can indeed boost indoor localization. The overall conclusion of the above analyses for Wi-Fi data has exhibited data properties and interconnections that aim to point out the most optimal selection of a Machine Learning algorithm capable of accurately classifying a location point based on Signal Strength data values. The next Section elaborates the selection.

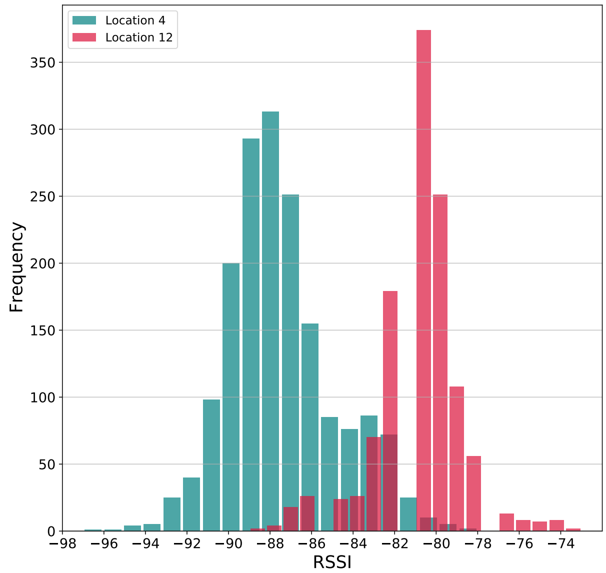

Fig. 3. Histogram of RSSI values from AP 2 for room A242 and A243 and location points 4 and 12.

IV. Neural Networks Model

During the past two decades, Artificial Neural Networks (ANN) have emerged as a cornerstone in machine learning, extensively applied across various domains for both predictive and classificatory functions [8]. Drawing inspiration from the biological neural networks of the brain, ANNs are devised as mathematical models to replicate the structure and functionality of their biological counterparts [39]. Their applications span various scientific fields, including but not limited to pattern recognition [40], image classification [41], language processing [42], computer vision [43], and time series forecasting [44].

ANN architecture is fundamentally composed of three layers: the input layer, hidden layers, and the output layer. The presence of multiple hidden layers signifies the depth of the network. These networks simulate brain learning by identifying latent correlations in input data through neurons in the hidden layers, where each neuron's output is relayed as input to subsequent layers. The performance of training and the predictive accuracy of an ANN are significantly influenced by the initial weighting of the connections and the choice of activation function [45]. Activation functions, which can be linear or nonlinear, are crucial in maintaining the neuron's output within a typical range of $[0, 1]$ or $[-1, 1]$, with nonlinear functions like Sigmoid, Rectified Linear Unit (ReLU), and Tanh being prevalent [46].

The Sigmoid function is characterized for its continuous differentiability but is criticized for its gradient vanishing issue, which can impede the learning process [45]. This challenge is addressed by the ReLU activation function that facilitates continuous learning progression, making it a preferred choice for neurons in hidden layers, while Sigmoid is favored for output layer neurons [45]. Neural networks operate on supervised learning principles, where neuron weights are adjusted during training to closely approximate ground truth.

TABLE II
SELECTION OF THE HYPER PARAMETERS FOR DESIGNING THE NN MODELS.

Hyper Parameter	*Values*
Number of neurons	Layer1-192, Layer2-96, Layer3-24
Learning rate	0.001, 0.01
Number of epochs	50
Batch size	64

The iterative training process involves a loss (cost) function to evaluate the network's performance with specific weights. For tasks involving multiple classes, such as localization, Categorical Cross-Entropy is frequently employed as a loss function for multi-class classification. Optimization algorithms, including Stochastic Gradient Descent (SGD), Adaptive Moment Optimization (Adam), and Root Mean Square Propagation (RMSProp), play a critical role in minimizing the loss function during training to efficiently fine-tune the weights of neurons.

A. Algorithm Evaluation Techniques

In the evaluation of predictive or classification algorithms, several standard metrics are routinely used to assess performance. For predictive tasks, the Mean Squared Error (MSE) and Mean Absolute Error (MAE) are commonly utilized metrics, formulated as:

$$MSE = \frac{1}{2m}\sum_{i=1}^{m}(\hat{y}^{(i)} - y^{(i)})^2. \tag{1}$$

$$MAE = \frac{1}{m}\sum_{i=1}^{m}|\hat{y}^{(i)} - y^{(i)}|. \tag{2}$$

The MSE metric serves as a measure for error estimation, with lower values indicating higher precision in estimation. It calculates the average of the squared discrepancies between predicted outcomes and actual values, while MAE quantifies the average magnitude of errors across predictions. Validation loss, furthermore, indicates the model's performance throughout the training phase.

For classification tasks, such as those in localization studies, the research community leverages specific metrics to gauge various aspects of a classifier's performance. These metrics include Confusion Matrix, Accuracy, F1 Score, Receiver Operating Characteristic Curve (ROC AUC) Accuracy, Average Precision (AP), and Top-k Accuracy.

- *Confusion Matrix*: This is an $N \times N$ matrix, where N is the number of distinct classes, that contrasts actual versus predicted classifications, offering a comprehensive view of the classification model's effectiveness and the nature of its errors.
- *Accuracy*: This metric measures the overall proportion of correct predictions made by the model, calculated as:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}, \tag{3}$$

where TP and TN represent correctly classified positive and negative instances, respectively, and FP and FN denote incorrectly classified negative and positive instances, respectively.

- *F1 Score*: Representing the harmonic mean of Precision and Recall, the F1 Score encapsulates both the accuracy of positive predictions and the rate at which positive instances are correctly identified [47], computed using:

$$F1\ score = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}. \tag{4}$$

The F1 Score varies within the $[0, 1]$ range, achieving its minimum and maximum in scenarios of perfect misclassification and flawless classification, respectively [48]. In multi-class scenarios, it is essential to incorporate a comprehensive measure of Precision and Recall for all classes into the harmonic mean, resulting in two versions: Micro F1 score and Macro F1 score.

- *ROC AUC*: The ROC curve, an evaluation tool for binary classifications, plots the True Positive Rate against the False Positive Rate [47]. The AUC value serves as a classifier's capability indicator to differentiate between classes, with a perfect classifier achieving an AUC of 1 [49].
- *Average Precision*: This metric integrates both Recall and Precision, presented as a recall function $p(r)$.
- *Top-k Accuracy*: Frequently used in machine learning, especially within deep neural network contexts, this metric assesses the likelihood that the correct class is among the top-k predictions. It is particularly relevant in fields like computer vision, indicating the model's predictive range.

B. Neural Network Model for Localization

The development of a Neural Network model for localization involved several critical steps, starting with the preprocessing of data, which included data normalization of the collected data. This initial stage adjusted for the varying scales of data values through normalization, focusing on the k collected RSS values from specific jth Wi-Fi Access Points as input at ith position, as depicted in Section III and shown in Figure 1. The objective was to predict sensor location i, which were classified into 25 distinct positions (ranging from $i \in \{0, \ldots, 24\}$). For this purpose, the input of 397 Wi-Fi access points was utilized for the Wi-Fi model. The dataset was then divided, assigning 10% for testing, and the remaining portion was further segmented into training and validation sets, the validation subset also comprising 10%.

To determine the most effective and accurate model configuration, various hyper-parameter combinations were evaluated. This included experimenting with the Adam optimizer alongside other parameters, which are detailed in Table II. The results of these experiments, particularly those related to the Wi-Fi Neural Network model, are summarized in Table III. Here, it was observed that a specific parameter set, comprising a learning rate of 0.001 and a training duration of 50 epochs, yielded the highest test set accuracy. The performance of the model, depicted in Figure 4, illustrates the progression of learning in both the training and validation phases, highlighting the increase in accuracy and the decrease in loss over time until the model converges.

Furthermore, a confusion matrix was generated for the model using a learning rate of 0.001 and 50 epochs with Wi-Fi

TABLE III
RESULTS OF FIRST NEURAL NETWORK MODEL USING SIGNAL STRENGTH DATA FROM WI-FI.

				Macro Avg			*Weighted Avg*		
	Learning Rate	*Epochs*	*Accuracy*	*Precision*	*Recall*	*F-Score*	*Precision*	*Recall*	*F-Score*
train	0.01	50	0.9307	0.9365	0.9065	0.9082	0.9424	0.9307	0.9260
val	0.01	50	0.9317	0.9398	0.9073	0.9139	0.9404	0.9317	0.9289
test	0.01	50	0.9287	0.9359	0.8999	0.9033	0.9404	0.9287	0.9239
train	0.001	50	0.9866	0.9834	0.9770	0.9793	0.9874	0.9866	0.9866
val	0.001	50	0.9831	0.9789	0.9708	0.9736	0.9841	0.9831	0.9831
test	*0.001*	*50*	*0.9864*	*0.9810*	*0.9781*	*0.9786*	*0.9873*	*0.9864*	*0.9864*

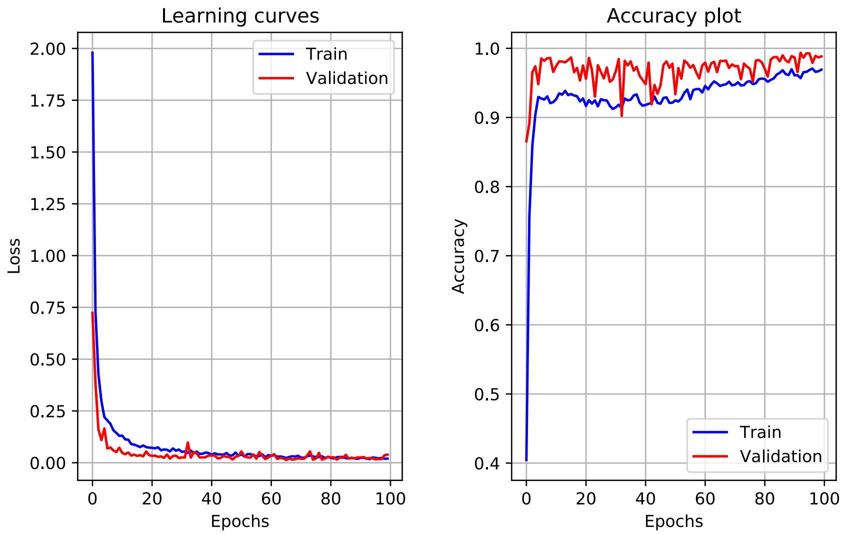

Fig. 4. Learning path of model with training and validation loss and Accuracy plot for Wi-Fi data.

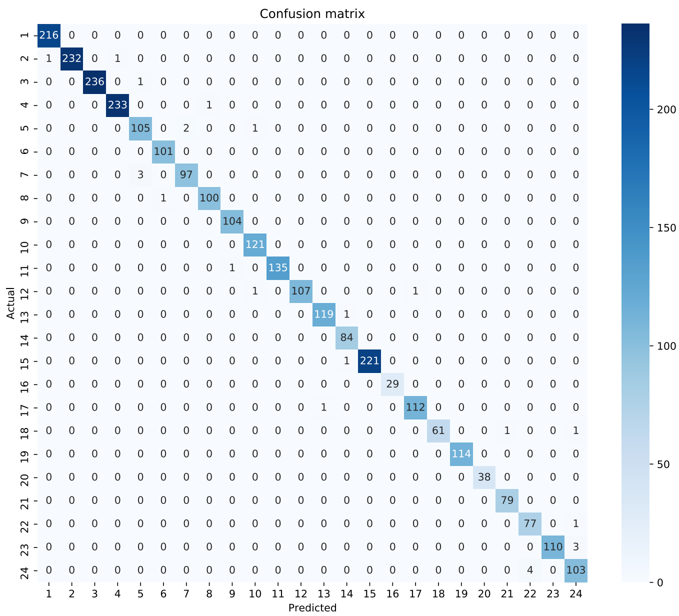

Fig. 5. Confusion matrix for 0.001 learning rate and 50 epochs and Wi-Fi data.

data, providing a detailed visual representation of its predictive accuracy across different locations, as shown in Figure 5. The axes of the confusion matrix are critical for understanding the performance and accuracy of our model. The vertical axis (y-axis) represents the actual classes, indicating the true locations as determined by our setup. These classes are segmented into distinct areas within the industrial environment, each labeled according to predefined zones of interest (positions 1-24 in Figure 2. The horizontal axis (x-axis) corresponds to the predicted classes, showcasing the output of our localization model. Similarly to actual classes, these predicted classes are categorized into the same zones, allowing for a direct comparison between where the model predicts that a device is located and its actual location. The cells within the matrix elucidate the number of predictions for each class, with the diagonal cells indicating correct predictions (true positives) where the model's predicted location matches the actual location. Off-diagonal cells represent misclassifications, where the model's predictions diverge from the true locations, categorized as either false positives or false negatives depending on the direction of the discrepancy. This confusion matrix is instrumental in quantifying the performance of our Wi-Fi-based localization method, providing information on its precision, recall, and overall accuracy in distinguishing between different zones within the industrial environment. Through this detailed breakdown, we can assess the model's strengths in correctly identifying specific areas and identify any potential areas for improvement in its predictive capabilities. The results presented in the Confusion matrix indeed reflect the training of our Neural Network model indicating that rather good localization accuracy in Industrial IoT environment can be obtained from observing the strength of the Wi-Fi signal from nearby access points.

For future work, transitioning towards employing TinyML presents an exciting avenue to explore [50]. TinyML enables the deployment of trained neural network models directly onto low-power edge devices, significantly reducing the computational and energy requirements. This shift could revolutionize the application of our Wi-Fi-based localization method by embedding the capability directly into edge devices deployed within the industrial environment. By integrating TinyML, we can leverage the lightweight and efficient models that run directly on edge devices, facilitating real-time localization without the need for constant communication with a centralized server or the use of high-performance computing resources. Such an approach not only promises to enhance the scalability and efficiency of our localization solution but also opens new possibilities for its application in scenarios where immediate data processing on the device is crucial.

V. Conclusion

This study presents a framework for the indoor localization of devices within Industrial Internet of Things (IIoT) environments, leveraging variations in wireless signal strength. Location estimation is achieved through Wi-Fi scanning, which collects data on nearby access points, including SSID, MAC address, and RSSI. Neural Networks (NN) were applied as the machine learning methodology for determining the device's position based on changes in signal strength. Evaluation of the collected data demonstrates that signal strength measurements, specifically RSSI values from Wi-Fi, can accurately pinpoint the location of a device with up to 98.6% accuracy. Future endeavors will focus on extending the duration of signal strength data collection to deepen understanding of its fluctuations. In addition, alternative machine learning algorithms will be explored. Furthermore, the machine learning models implemented will be deployed on microcontrollers to assess the precision of real-time device localization. Finally, exploring the usage of TinyML will allow the deployment of trained neural network models directly onto low-power edge devices, significantly reducing the computational and energy requirements, which is planned for future work.

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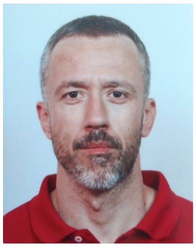

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