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Performance Evaluation of an Artificial Neural Network Model for RSSI-Based Indoor Localization of Workplace Assets

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Abstract*— The inefficiency of conventional manual methods for tracking work equipment often results in asset record inaccuracies and time-consuming physical inventory processes. This research evaluates the performance of an Artificial Neural Network (ANN) implemented within a Bluetooth Low Energy (BLE)-based Indoor Positioning System (IPS) that leverages Received Signal Strength Indicator (RSSI) data. The proposed system utilizes a Multilayer Perceptron (MLP) with a 3-14-7-3 configuration, featuring Rectified Linear Unit (ReLU) activations in its hidden layers and a Softmax function at the output, optimized using the Adam algorithm. The model was trained and validated on a balanced dataset comprising 600 RSSI samples collected from three distinct rooms, divided into 80% for training and 20% for testing. The experimental results reveal a high-performing model, achieving an accuracy of 90.83%, a precision of 90.88%, a recall of 90.83%, an F1-Score of 90.85%, and a Mean Absolute Error (MAE) of 0.1083. These outcomes confirm the ANN's robust capability to interpret the complex, non-linear signal fluctuations typical of indoor environments for reliable device localization.

***Index Terms*— Indoor Positioning System, Bluetooth Low Energy, RSSI, Artificial Neural Network, Work Device Localization.**

I. INTRODUCTION

The development of digital technology in the Industry 4.0 era encourages various industrial sectors to adopt data-based and artificial-intelligence technologies to improve operational efficiency and productivity (Suyanto & Utama, 2021). The application of the Internet of Things (IoT), Artificial Intelligence (AI), and Machine Learning has become one of the widely used efforts to support digital transformation, particularly in data and asset management (Pratama & Handoko, 2022). In the industrial context, the use of smart technology is also in line with the need for more effective and sustainable resource management, including in work-device inventory systems (Ramadhan & Setiawan, 2023).

Information-technology asset management is an important aspect of maintaining smooth company operations (Kusuma & Hidayat, 2021). Besides serving as inventory documentation, asset management also aims to ensure conformity between inventory data and actual field conditions (Fasya et al., 2023). Based on observations of the work-device audit process, devices are still found that are not located according to inventory data, so the search has to be carried out manually from one room to another. This condition makes the audit process less efficient, especially when the number of devices being checked is quite large or devices change location without an update to the inventory data (Kusuma & Hidayat, 2021).

One approach that can be applied to help identify the location of devices inside a room is the Indoor Positioning System (IPS) (Nugraha & Sukma, 2024). Unlike the Global Positioning System (GPS), which has limitations in indoor environments, IPS utilizes the characteristics of wireless signals to determine the location of an object. In this system, the parameter that is often used is the Received Signal Strength Indicator (RSSI) because it is easy to obtain without requiring high-cost devices (Farahiyah & Reza, 2021; Siregar & Arisandi, 2023). However, the RSSI value is strongly influenced by distance, obstacles, signal interference, and environmental conditions, resulting in fluctuating data with a non-linear relationship to the actual position (Siregar & Arisandi, 2023).

The complex characteristics of RSSI data cause conventional threshold-based approaches or signal-propagation models to often produce unstable location estimates (Nugroho & Lestari, 2024). Therefore, a method is needed that can adaptively learn the relationship between RSSI values and device location. One method with this capability is the Artificial Neural Network (ANN) (Al Fadil et al., 2026). ANN is able to learn non-linear patterns from a dataset through a training process, so that it can recognize the relationship between combinations of RSSI values and device location without having to build a complex mathematical model (A. Wibowo & Rahmawati, 2020). This capability makes ANN a potential method for improving location-classification performance in RSSI-based Indoor Positioning Systems (Setiawan & Christian, 2025).

Based on a review of previous studies, a research gap still exists in the analysis of ANN application for work-device localization in office environments (Hidayat & Nugroho, 2023). Most previous studies have focused more on developing general localization systems or comparing the accuracy of several classification algorithms, while the object generally used is the user or a smartphone. This study positions the work device as the tracking object and focuses the analysis on the ability of ANN to recognize RSSI patterns from three reference points in order to classify the location of work devices in three different rooms. Thus, the novelty of this research lies in the analysis of ANN application in BLE-based IPS to support work-asset audits more precisely, efficiently, and accurately (S. A. Wibowo & Cahyono, 2021).

This study aims to analyze the characteristics of the RSSI data used as input for the ANN model, analyze the application of ANN mathematical concepts in the model implementation for work-device location classification, analyze the compatibility between the mathematical concepts and the model implementation results, and analyze the model's performance based on Accuracy, Precision, Recall, F1-Score, the Confusion Matrix, and the loss curve (Haryanto & Setiawan, 2020).

II. Method

A. Research Design

This study is an experimental research that aims to analyze the application of an Artificial Neural Network (ANN) in a Bluetooth Low Energy (BLE)-based Indoor Positioning System (IPS) using the Received Signal Strength Indicator (RSSI) parameter to classify work-device locations. The research stages include system design, RSSI data collection, data preprocessing, ANN model training, and model-performance evaluation based on Accuracy, Precision, Recall, F1-Score, the Confusion Matrix, and the loss value. The research flow is shown in Fig. 1

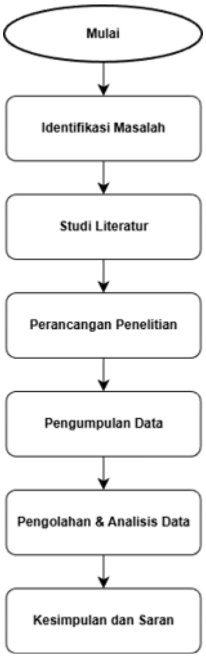

Fig. 1. Research flow Diagram

B. System Architecture

The Indoor Positioning System developed consists of one work device that transmits a Bluetooth Low Energy (BLE) signal and three receiver devices placed in three different rooms. Each receiver is built using an ESP32 microcontroller integrated with a TFT LCD screen and a buzzer as an indicator. The three receivers capture the Received Signal Strength Indicator (RSSI) value from the work device; the data is then collected and processed through a preprocessing stage before being used as input to the Artificial Neural Network (ANN) model to determine the location of the work device. The system architecture used in this study is shown in Fig. 2.

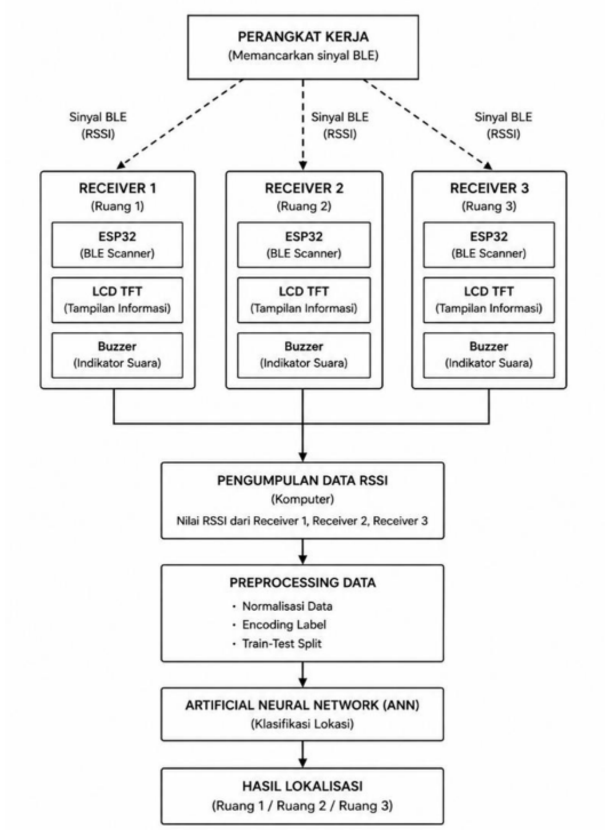

Fig. 2. Block diagram of the BLE- and ANN-based Indoor Positioning System

C. Data Collection

Data collection was carried out in the three rooms that constituted the research area. The work device transmits a BLE signal as the transmitter, while three devices equipped with an ESP32 microcontroller are used as receivers to capture the RSSI value. Data was collected at various device positions to obtain a variation of RSSI values representing the actual conditions of the indoor environment.

Each data record consists of three RSSI attributes originating from each ESP32 and one location label indicating the position of the work device. The dataset obtained was then used as training and testing data for the ANN model. Table 1 shows the specifications of the data-collection process.

TABLE I. DATA COLLECTION SPECIFICATIONS

Parameter	Value
Number of rooms	3
Number of receivers	3
Number of work devices	120

D. Data Preprocessing

The preprocessing stage was carried out to improve data quality before it was used in the model-training process. The steps taken included checking for missing data, class labeling, standardization using the Z-score method, and dividing the

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dataset into training and testing data with an 80:20 ratio. Standardization was performed using Eq. (1).

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}} \quad (1)$$

where Zscore is the output feature value after standardization, x is the raw RSSI signal-strength value (dBm), μ is the population mean, and σ is the population standard deviation.

E. Artificial Neural Network Model Design

The ANN model used is a Multilayer Perceptron (MLP) with three neurons in the input layer representing the RSSI values from the three ESP32 units, two hidden layers consisting of 14 and 7 neurons respectively, and three neurons in the output layer representing the three location classes of the work device. The activation function used in the hidden layers is the Rectified Linear Unit (ReLU), while the output layer uses the Softmax function. The training process was carried out using the Adam Optimizer with a learning rate of 0.001 for 50 epochs.

The feedforward process is calculated using Eq. (2).

$$Z_j = \sum_{i=1}^{n} x_i w_{ij} + b_j \quad (2)$$

The ReLU activation function is expressed in Eq. (3).

$$f(x) = max(0, x) \quad (3)$$

The output layer uses the Softmax function as shown in Eq. (4).

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}} \quad (4)$$

The model architecture is shown in Fig. 3.

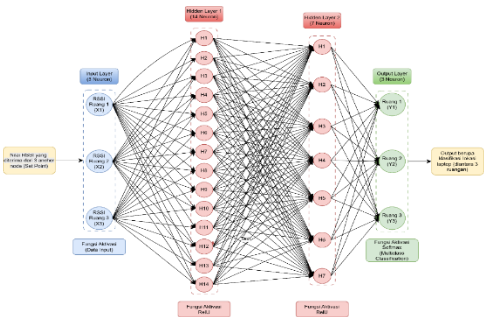

Fig. 3. Neural-network architecture

F. Model Evaluation

Model performance was evaluated using the Confusion Matrix, Accuracy, Precision, Recall, and F1-Score. In addition, the loss curve during the training process was also analyzed to determine the model's convergence ability.

Accuracy is calculated using Eq. (5).

$$Accuracy = (Correct\ Predictions / Total\ Data) \times 100 \quad (5)$$

Precision is calculated using Eq. (6).

$$Precision = TP / (TP + FP) \quad (6)$$

Recall is calculated using Eq. (7).

$$Recall = TP / (TP + FN) \quad (7)$$

F1-Score is calculated using Eq. (8).

$$F1\text{-}Score = 2 \times (Recall \times Precision) / (Recall + Precision) \quad (8)$$

III. RESULTS AND DISCUSSION

A. System Implementation Results

The receiver device was successfully implemented using an ESP32 microcontroller integrated with a TFT LCD screen and a buzzer as an indicator. The receiver is able to scan the Bluetooth Low Energy (BLE) signal transmitted by the work device and display the scanning results on the TFT LCD screen in real time. In addition, the buzzer functions as an indicator when the scanning process is successfully carried out. The implementation result of the device is shown in Fig. 4.

Fig. 4. Receiver device

B. ANN Model Training Results

The Artificial Neural Network model used has a 3-14-7-3 architecture consisting of three neurons in the input layer, two hidden layers with 14 and 7 neurons, and three neurons in the output layer. The training process was carried out using the Adam optimizer and the ReLU activation function. Based on the training results, the loss value gradually decreased until it reached a convergent condition, as shown in Fig. 5. This shows that the model is able to effectively learn the relationship between RSSI values and the work-device location classes.

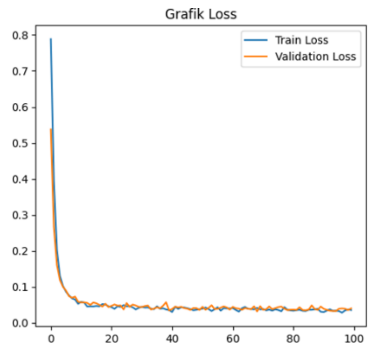

Fig. 5. Loss curve

C. Model Evaluation Results

Table 2 shows the ANN model evaluation results.

TABLE II. EXPERT VALIDATION RESULTS

Parameter	**Value**
Accuracy	90.83%
Precision	90.88%
Recall	90.83%

F1-Score	90.85%

The confusion matrix for the testing data is shown in Fig. 6.

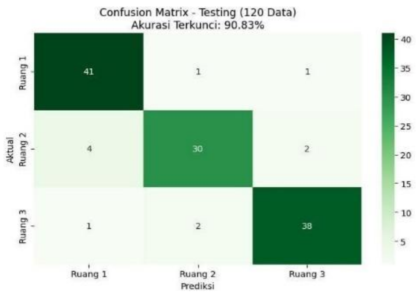

Fig. 6. Confusion matrix

D. ANN Application Analysis

The results show that ANN is able to learn the non-linear relationship between RSSI values and work-device location. Although the RSSI value fluctuates due to physical obstacles and signal interference, the learning process through the backpropagation algorithm allows the model to adjust its weights so that the pattern of each room can be recognized well. This shows that ANN is more adaptive compared with threshold-based methods, which are highly sensitive to changes in the RSSI value.

IV. Conclusion

This study successfully analyzed the application of an Artificial Neural Network (ANN) in a Bluetooth Low Energy (BLE)-based Indoor Positioning System (IPS) for work-device localization using the Received Signal Strength Indicator (RSSI) value. The ANN model developed showed good classification performance with an accuracy rate of 90.83%, so it is able to learn the fluctuating RSSI patterns found in indoor environments. The main contribution of this study is to show that ANN can be applied as an effective method to support the work-device localization process, thereby having the potential to improve the efficiency of asset management and auditing in office environments.

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