

Assessment Of Neural Networks Localization Using RSSI & CSI

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Abstract—Underground mining localization is challenging due to the inoperability of GPS and harsh environmental conditions. This study compares the performance of FCNN, MLP, and LSTM neural networks in predicting X and Y coordinates using RSSI and WiFi-based CSI data collected in a mining tunnel under both LOS and NLOS conditions. Experimental results show that FCNN outperforms MLP and LSTM by achieving the highest accuracy, lowest errors (RMSE, MAE), and the best R^2 scores. The findings highlight FCNN's potential for localization in GPS-denied environments. Future research may explore hybrid neural networks and real-time localization systems.

I. INTRODUCTION

Accurate localization is essential in fields such as telecommunications, transportation, and emergency management. However, in underground mining tunnels, traditional GPS systems are ineffective due to harsh conditions like dust, humidity, and weak signals, necessitating alternative solutions [1]. RSSI-based techniques using low-cost ESP32 sensors have shown potential for improving localization by estimating position through signal strength measurements [2]. Recent advancements in AI, including Deep Neural Networks (DNN) and Multi-Layer Perceptrons (MLP), have enhanced localization accuracy by learning complex data patterns, even under challenging conditions [3], though environmental variability remains a significant factor [4]. This study explores the use of ESP32 devices [5] to collect RSSI and CSI data in an underground tunnel and evaluates three machine learning models for localization: Fully Convolutional Neural Networks (FCNN): chosen for its ability to process high-dimensional data and achieve high accuracy without spatial or temporal constraints. Multi-Layer Perceptron (MLP): used as a baseline based on the 2024 study by Khalaf, Kandil, and Hakem, showing effectiveness in modeling nonlinear relationships. Long Short-Term Memory (LSTM) networks to assess the impact of capturing temporal dependencies in sequential RSSI and CSI data. The dataset was collected in a gold mine tunnel at "La Cité de l'Or," Canada, using ESP32 modules [5] at 2.4 GHz with a 40 MHz bandwidth. It comprises RSSI, CSI, and X/Y coordinates from 303 points under both LOS and NLOS conditions, totaling 45,164 measurements—offering a solid foundation for evaluating localization and prediction in mining environments.

II. MODELS AND ARCHITECTURES

This project implements and compares three neural network models—FCNN, MLP, and LSTM—to predict spatial coordinates (X, Y) from collected data. FCNN processes input globally without emphasizing temporal or spatial relationships,

while MLP captures complex hierarchical features through its hidden layers. LSTM leverages temporal dependencies, making it well-suited for sequential datasets. The models are evaluated in terms of prediction accuracy, computational efficiency, and robustness, providing insights into their respective strengths and limitations for coordinate prediction in this application [5].

A. FCNN, MLP, and LSTM Networks

In this study, three neural network models—FCNN, MLP, and LSTM—were implemented for localization tasks using normalized data split into 80% training and 20% testing. The FCNN model consists of three hidden layers (512, 256, 128 neurons) with ReLU activation, Batch Normalization, and 30% dropout, trained for 100 epochs using the Adam optimizer (learning rate: 0.001) and MSE loss. It predicts X and Y coordinates via a linear output layer and is evaluated using RMSE, MAE, and R^2 metrics. The MLP model, with hidden layers of 256, 128, and 64 neurons and similar preprocessing, also predicts X and Y coordinates and is evaluated using the same metrics. The LSTM model reshapes input into 3D for sequential data processing and includes two LSTM layers (64 and 128 neurons with tanh and sigmoid activations), Batch Normalization, 30% dropout, and a dense ReLU layer. It also uses a linear output layer and is trained with the same optimizer and loss function, showcasing its ability to handle sequential data effectively.

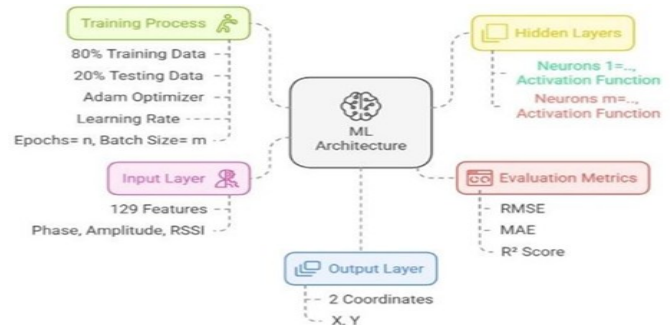


Figure. 1. Neural Network Architecture for Localization.

III. EVALUATION AND RESULTS

A. RMSE, MAE, and R^2 for Models

After training the FCNN, MLP, and LSTM models using RSSI and CSI data, their performance was evaluated using RMSE and MAE metrics for X and Y coordinate prediction. As shown in Table 1, FCNN achieved the highest accuracy with the lowest RMSE and MAE values. MLP showed moderate

performance, while LSTM was the least accurate, especially for the Y-coordinate. The evaluation was conducted on 100 randomly selected test points to ensure unbiased results.

TABLE I. PERFORMANCE COMPARISON RMSE & MAE FOR X/Y PREDICTIONS (FCNN, MLP, LSTM).

Model	RMSE (X) (meters)	RMSE (Y) (meters)	MAE (X) (meters)	MAE (Y) (meters)	R ² Score (X)	R ² Score (Y)
FCNN	0.1739	1.8552	0.0813	1.1390	0.9497	0.9825
MLP	0.2109	2.1104	0.1004	1.2841	0.9260	0.9774
LSTM	0.2417	2.4833	0.1014	1.4440	0.9028	0.9687

The FCNN model achieved the highest R² scores for both X and Y coordinates, indicating the most reliable performance. MLP showed slightly lower but still strong scores, while LSTM had the weakest results. The higher prediction error for the Y coordinate is attributed to its larger scale (~50 m) compared to X (~2.5 m), making Y more challenging to predict accurately.

B. Actual vs Predicted Y Comparison

As shown in Figure 2, a comparison image between the actual values and the predicted values for 100 test points shows that the blue dots represent the actual values, while the red marks represent the predicted values for both the X and Y coordinates. It can be seen from the figure that the FCNN model was the most accurate in predicting the actual values, the prediction points were much closer to the real values compared to other models, while the LSTM model showed a clear deviation from the actual values.

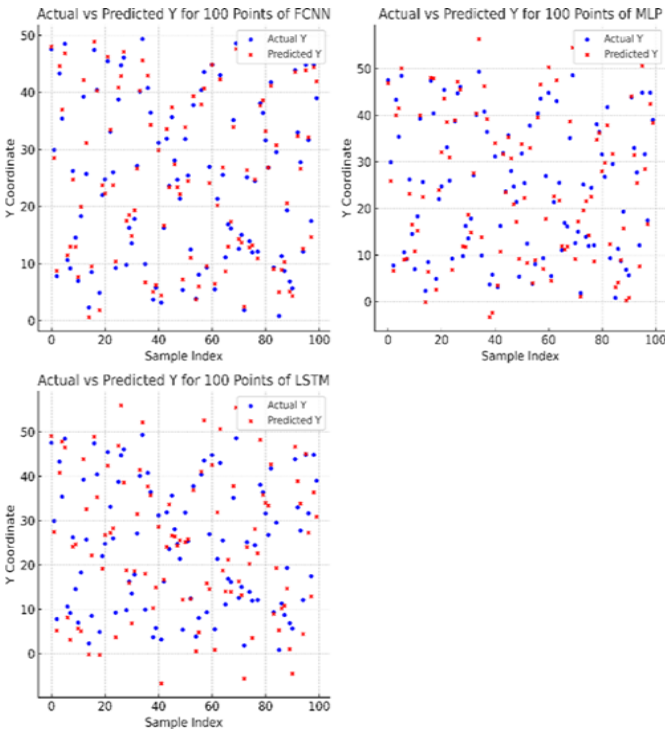


Figure 2. Actual vs Predicted Values Comparison for 100 Test Point.

C. Actual vs Predicted Locations Comparison models

Figure 3 compares the actual location at X = 0.0 m and Y = 29 m with the predicted locations from the FCNN, MLP, and

LSTM models. The actual location is marked by a black dot, with predictions shown by a blue marker (FCNN), an orange triangle (MLP), and a green box (LSTM). The FCNN model was closest to the actual point, showing minimal deviation, followed by MLP with moderate error, while LSTM had the largest deviation.

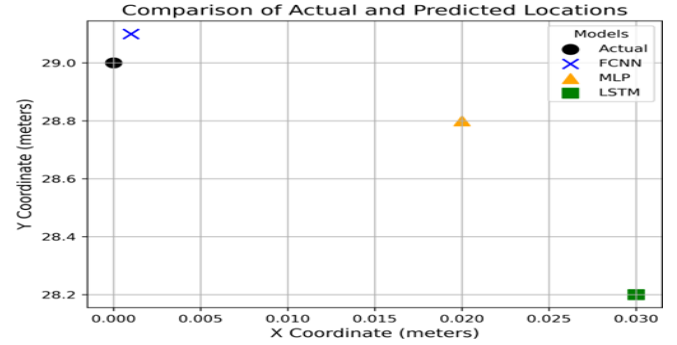


Figure 3. Actual Location vs Predicted Locations by FCNN, MLP, and LSTM.

Based on the results in Table 1 and Figures 2 and 3, the FCNN model is recommended for positioning applications requiring high accuracy, as it achieved the lowest error rates and the closest predictions to actual values.

IV. CONCLUSION AND FUTUR WORK

Accurate underground localization is challenged by signal attenuation and multipath effects. This study evaluated FCNN, MLP, and LSTM models using RSSI and CSI data to predict X and Y coordinates. FCNN achieved the best performance, with the lowest RMSE (0.17 m for X, 1.85 m for Y), lowest MAE (0.08 m for X, 1.14 m for Y), and highest R² scores (0.95 for X, 0.98 for Y). MLP showed moderate accuracy, while LSTM performed the weakest, especially for Y-coordinate predictions. These results highlight FCNN's effectiveness for reliable localization in GPS-deprived environments. Future work will explore hybrid models and real-time deployment for improved accuracy.

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