“Indoor Fingerprinting Based on Deep Neural Network and Random Forest with Calibrated Wi-Fi FTM "

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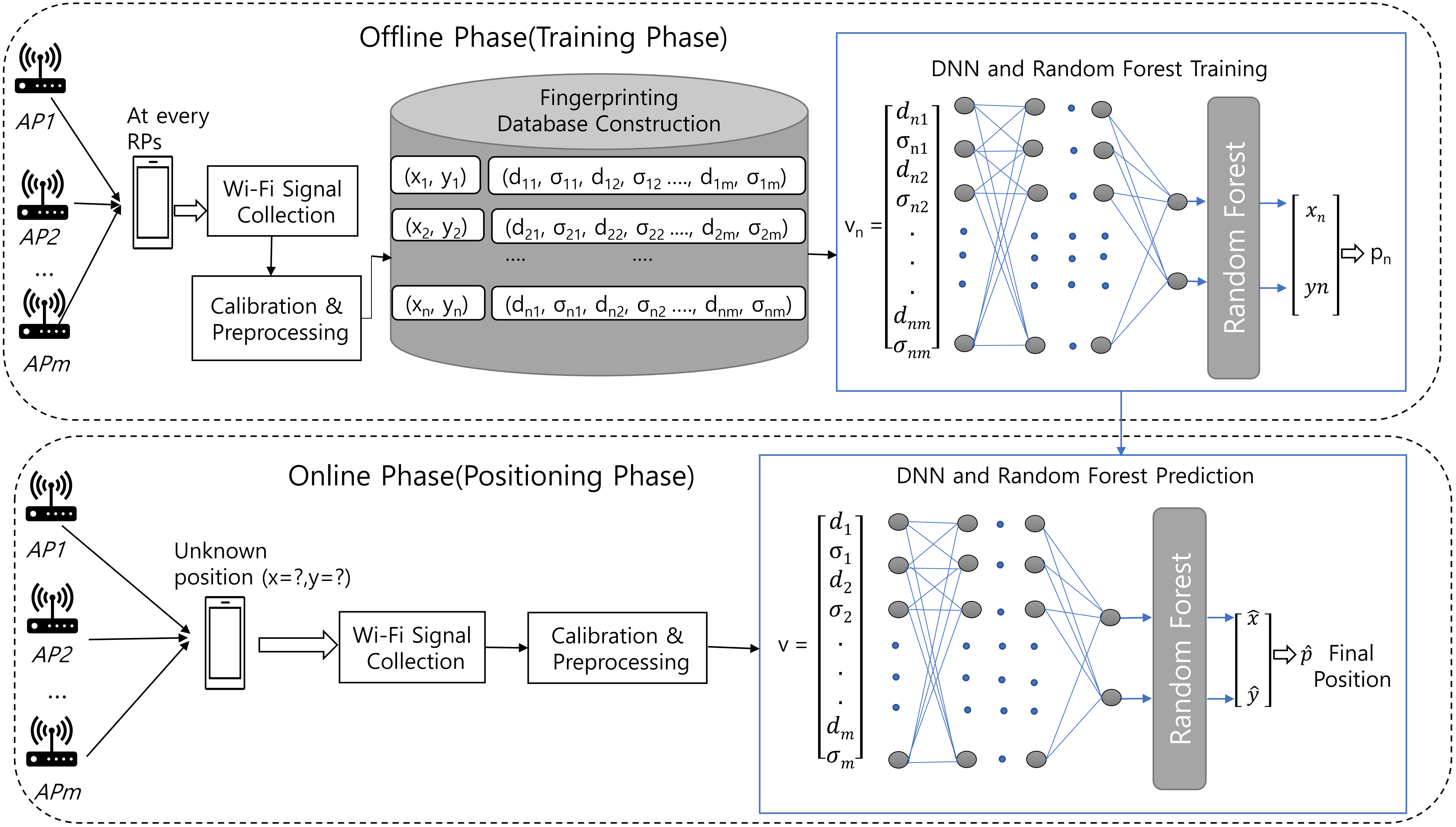
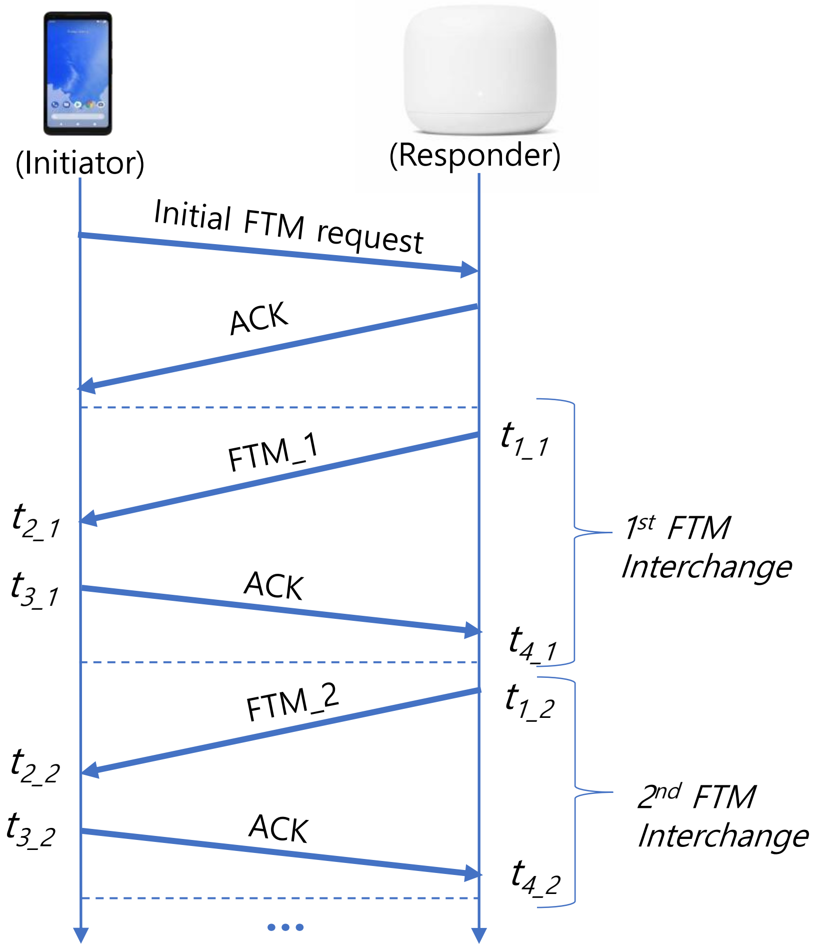
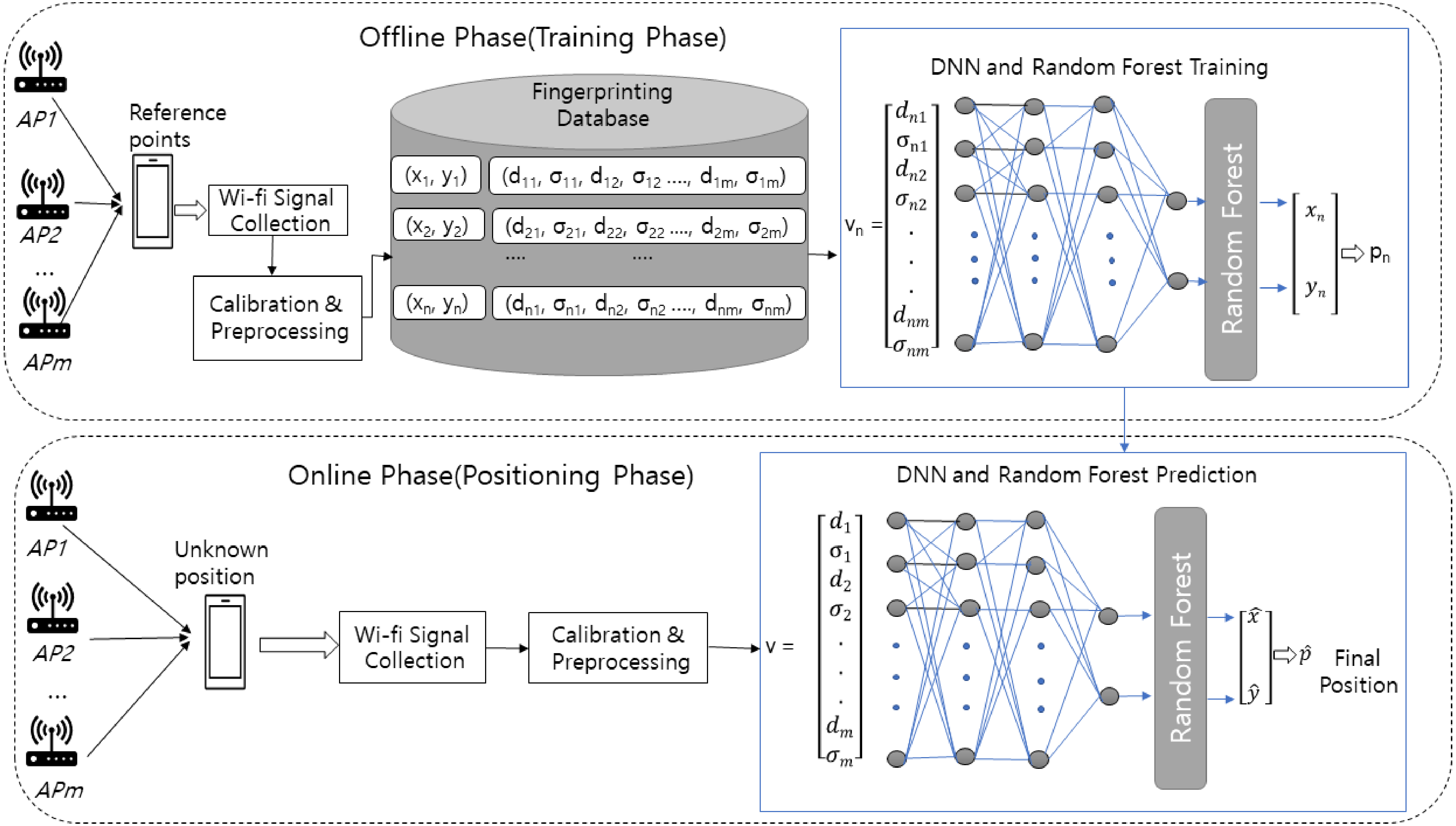
Contents



Offline Phase(Training Phase)
AP1
AP2
...
APm
At every RPs
Wi-Fi Signal Collection
Calibration & Preprocessing
Fingerprinting Database Construction
(x1, y1)
(d11, σ11, d12, σ12 ...., d1m, σ1m)
(x2, y2)
(d21, σ21, d22, σ22 ...., d2m, σ2m)
....
(xn, yn)
(dn1, σn1, dn2, σn2 ...., dnm, σnm)
DNN and Random Forest Training
vn =
Random Forest
pn
Online Phase(Positioning Phase)
AP1
AP2
...
APm
Unknown position (x=?,y=?)
Wi-Fi Signal Collection
Calibration & Preprocessing
DNN and Random Forest Prediction
v =
Random Forest
Final Position


(Initiator)
(Responder)
Initial FTM request
ACK
FTM_1
t_{1_1}
t_{2_1}
t_{3_1}
ACK
t_{4_1}
1st FTM Interchange
FTM_2
t_{1_2}
t_{2_2}
t_{3_2}
ACK
t_{4_2}
2nd FTM Interchange
...

Parameters	Values
Number	



Offline Phase(Training Phase)
AP1
AP2
...
APm
Reference points
Wi-fi Signal Collection
Calibration & Preprocessing
Fingerprinting Database
(x1, y1) (d11, σ11, d12, σ12 ...., d1m, σ1m)
(x2, y2) (d21, σ21, d22, σ22 ...., d2m, σ2m)
(xn, yn) (dn1, σn1, dn2, σn2 ...., dnm, σnm)
DNN and Random Forest Training
vn =
Random Forest
pn
Online Phase(Positioning Phase)
AP1
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Unknown position
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Introduction

- Wi-Fi-based ranging systems is a popular choice due to their wide availability and low cost for Indoor applications.
- Wi-Fi Round-Trip-Time (RTT) measurements have shown promise in providing accurate distance measurements.
- Accuracy of these measurements can be affected by several factors such as noise and interference in communication.
- Main motives:
  - To address the limitations of existing range estimation techniques.
  - To provide a more accurate and reliable solution for indoor localization, tracking, and navigation systems.

Theoretical Background

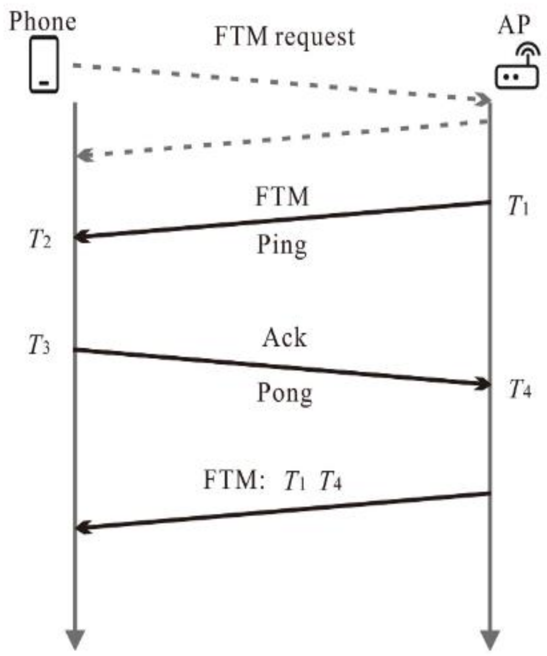
- Wi-Fi RTT (IEEE 802.11mc) is based on Time-of-Flight (ToF).
- In Wi-Fi RTT, the signal used for ToF measurements is the “Fine Timing Measurement" (FTM) frame.
- Can calculate distance between smartphone and AP by using RTT

$$RTT = (t_4 - t_1) - (t_3 - t_2)$$

Distance between the AP and smartphone can be obtained as follows:

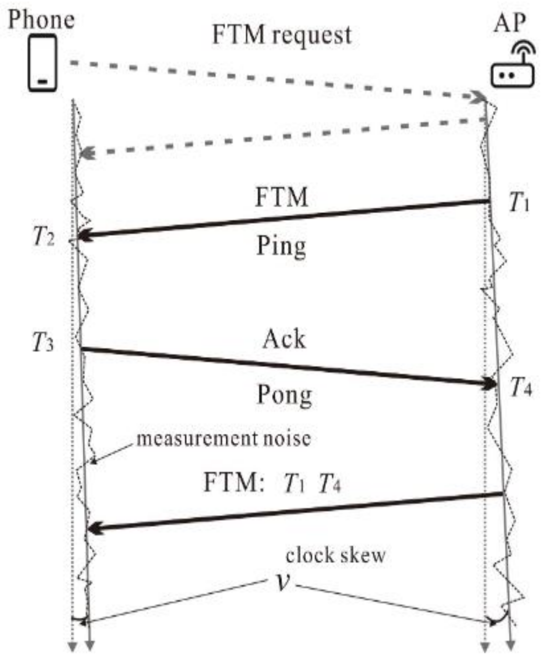
$$Range_{RTT} = \frac{RTT}{2} \cdot c$$

C is the speed of light in m/s



Theoretical Background

- All clock systems in nature suffer from skew, drift, and jitter.
- Clock skew can occur due to the difference in clock freque ncies of devices or due to clock drift.
- Device synchronization using IEE 8021.11mc, so clocks may drift or skew over time.
- Measurement Noise also occurred due to random variation or error caused by device hardware, signal propagation, and environmental conditions.
- Jitter is the deviation from the ideal or expected timing of a clock signal caused by various factors such as noise, inter ference, and other sources of signal distortion.



Theoretical Background

- Offset data can be calculated by using periodic offset calibration.

- Collection of time-series RTT range readings at each reference point is used to calibrate the range d_{offset} which is calculated as follows:

$$d_{offset} = \frac{1}{n}\sum_{k=1}^{n}(d_{m,k} - d)$$

where $d_{m,k}$ measurement at the reference point, and d is the geometric range between the transmitter

- Finally, RTT range can be found by the following:

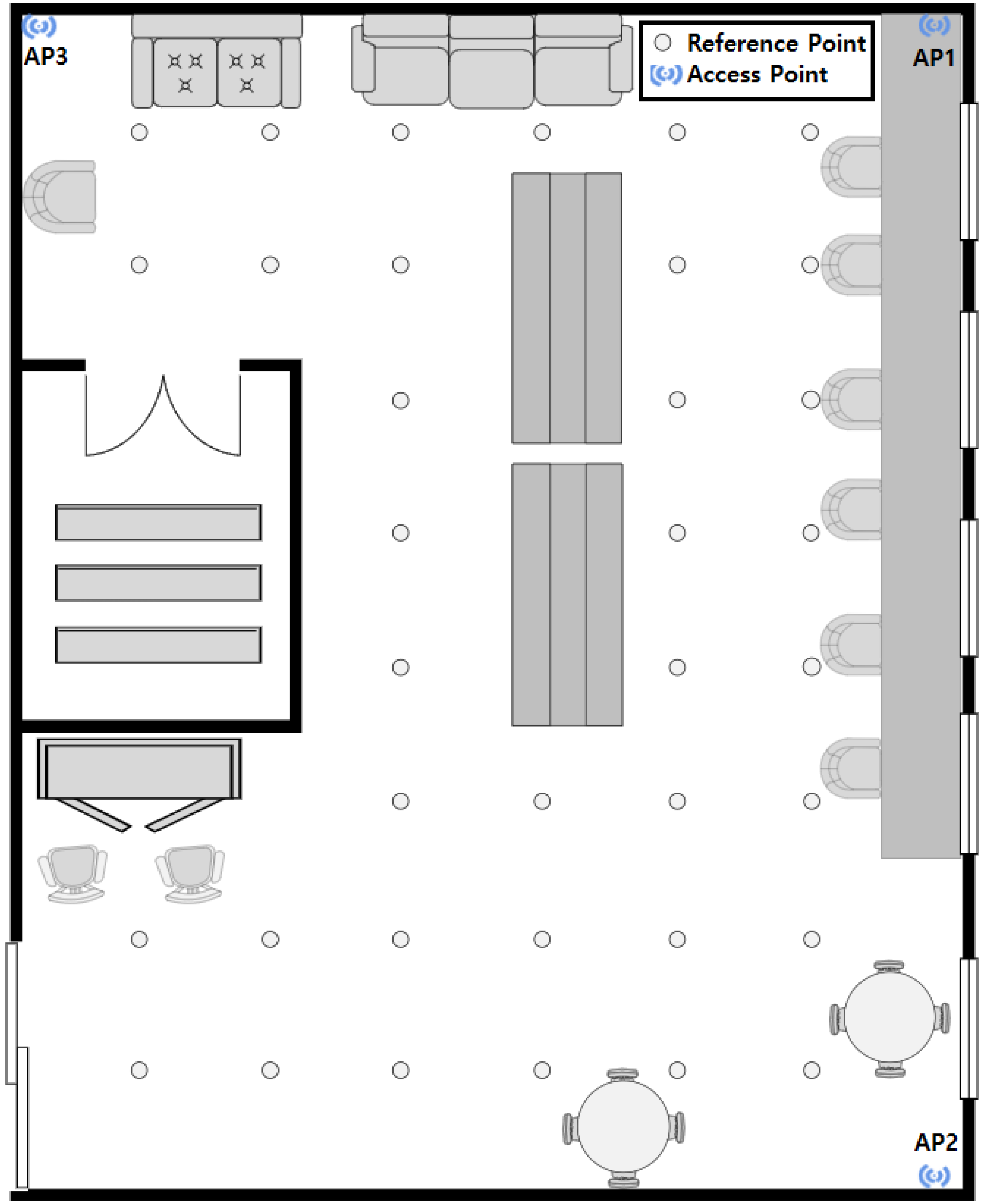
  $d = d_m - d_{offset} + W$ where W is the random measurement noise(Guo et al., 2019)

Wi-Fi RTT Data Acquisition

- Collected Wi-Fi Round-Trip-Time (RTT) measurements between a mobile device and google Wi-Fi access points (AP).
- Constructed the Reference points(RP) at every 1 m up to 25m and took the sample of RTT.
- The lowest latency of sending ranging requests from on RTT enabled smartphone is 100ms in theory.
- Google recommended that the sampling interval should not be shorter than 200 ms to avoid collisions and other software problems. (Dong et al., 2022)
- Set the 200 ms latency, which means one sample per 200 ms.
- At least 300 samples were collected at each RPs.

Wi-Fi RTT Data Acquisition

- One smartphone Google Pixel 2 and Google Pixel Nest Wi-Fi Router as an Access point.
- Used an android application named WifiRttScan developed by Google to send ranging requests and collect the ranging results.
- Collected the RTT and RSS measurements in each access point.



Wi-Fi RTT Data Acquisition

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- Used an android application named WifiRttScan developed by Goog le to send ranging requests and collect the ranging results.

Device Name	Chipset/ Wi-Fi Standard
Google Pixel 2	Snapdragon 835 Android 11
Google Nest WiFi	AC2200 4*4 MUMIMO Wi-Fi Dual band (2.4 GHz/5 GHZ)

Figure: Used device specifications

Data Preprocessing and Filtering

- Outlier detection on RTT measurement using Z Scores.
- Z score measures how many standard deviations an observation is from the mean of the range measurement.
- Calculate Z score for each data point: Z = (x - mean) / standard deviation.
- A Z score greater than a certain threshold(used 1) indicates an outlier.
- Remove outliers if they are errors or irrelevant to the analysis by considering data is normally distributed.

Data Preprocessing and Filtering

- After Outlier removal, applied the Kalman Filter to the RTT and RSSI measurements.
- Kalman filter is a highly efficient recursive filter that estimates the state of a dynamic system from a series of inaccuracies and noise-containing measure ments.
- We considered the measurement error and system model to be Gaussian or normal for using Kalman Filter.
- We set the parameter measurement noise covariance to 0.01 and process n oise covariance to the variance of measurements.

DNN Model Architecture

- DNN consists of three types of layers: input layer, hidden layer, and output layer.
- After doing preprocessing and Kalman with the proper label for supervised learning, divided the data as a train: test sets in 0.7:0.3.
- After this dataset were standardized for the input of DNN model.

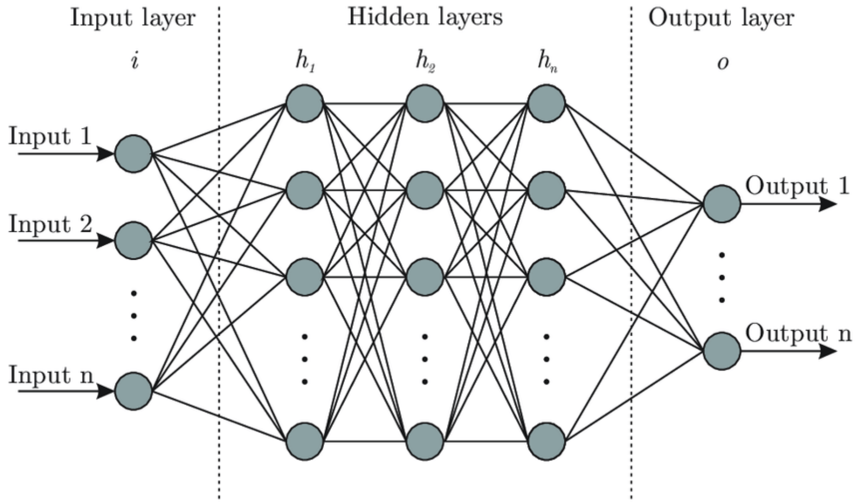


Figure: DNN model architecture

DNN-based Range Estimation Model

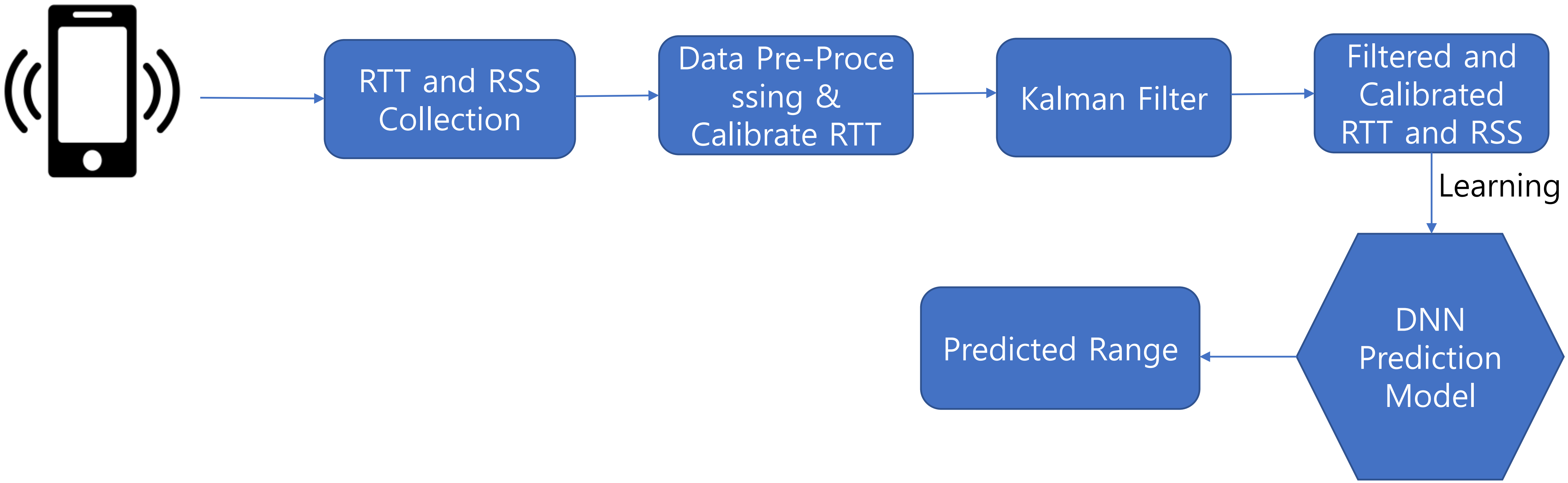


Figure: DNN-based Range Estimation Model

DNN-Based Range Estimation Model

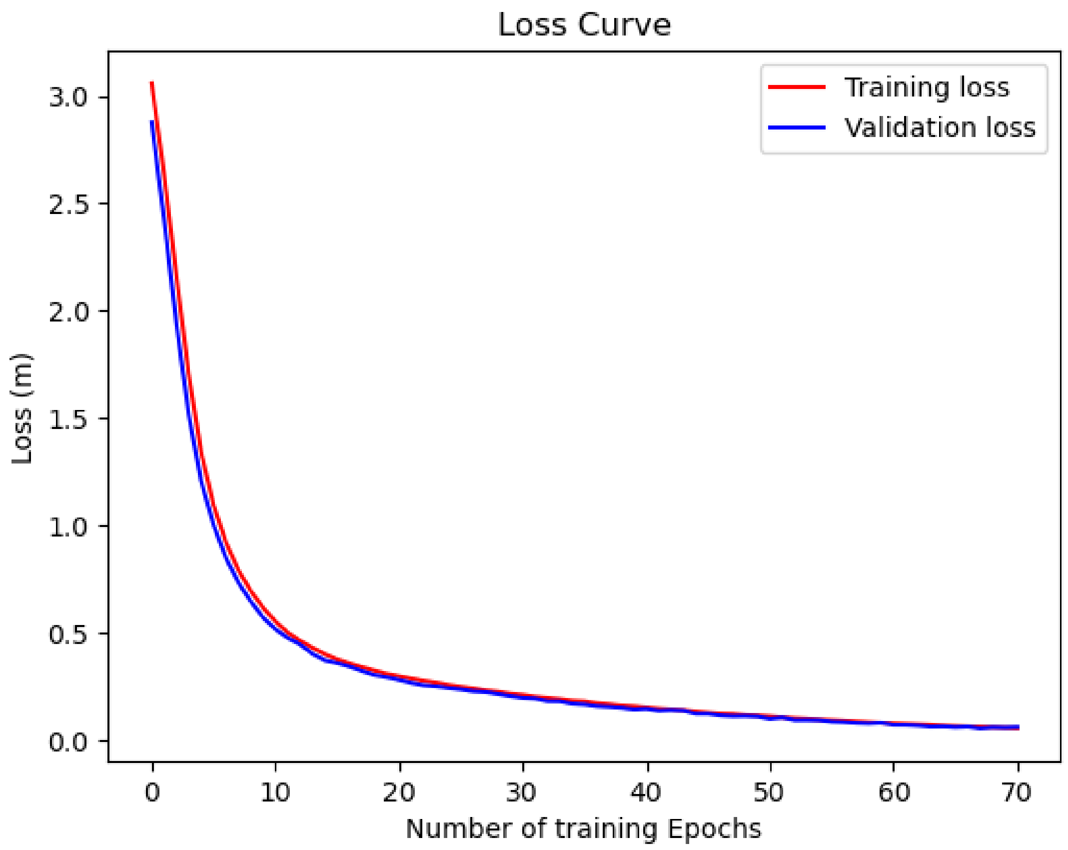
- Created a densely connected sequential DNN with 3 hidden layers with one 64, two 128 nodes, and an output layer with 25 nodes.
- One-Hot encoding is used to classify the classes in the output layer.
- In the hidden layer, we used Rectified Linear Unit(ReLU) as an activation function and softmax with categories in the output layer.
- Adam optimizer with a learning rate of 0.0001 was used with categorical_crossentropy as a loss function and with 'accuracy' metrics.
- Proposed learning system verification results were obtained by using Python 3.10.10 and TensorFlow 2.11.0 frameworks for AI learning model verification.

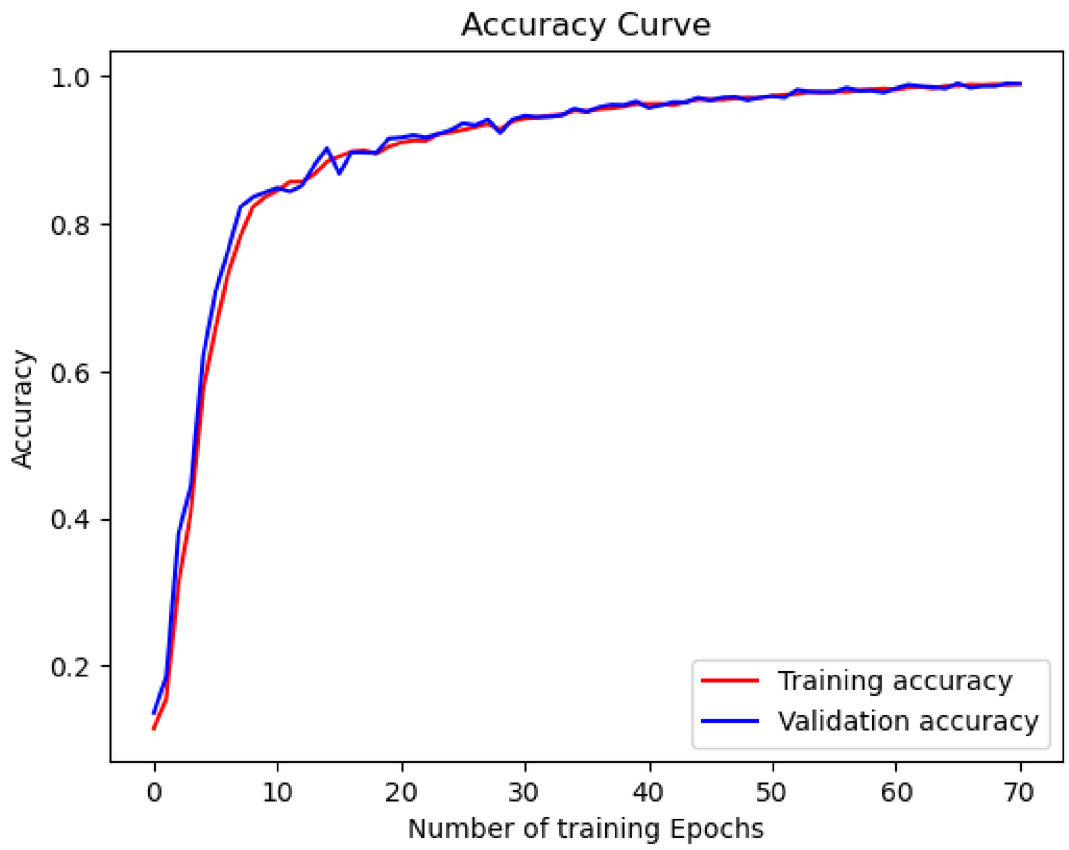
DNN-Based Range Estimation Model

- Early stopping technique with patience 3 epochs applied to the model during training.
- It prevent overfitting, improve the generalization and reduce the training time.
- It works by monitoring the performance of the model on a validation set during training.
- Patience is the number of epochs that the model is allowed to continue training without improvement before the training process is stopped.

Result and Analysis

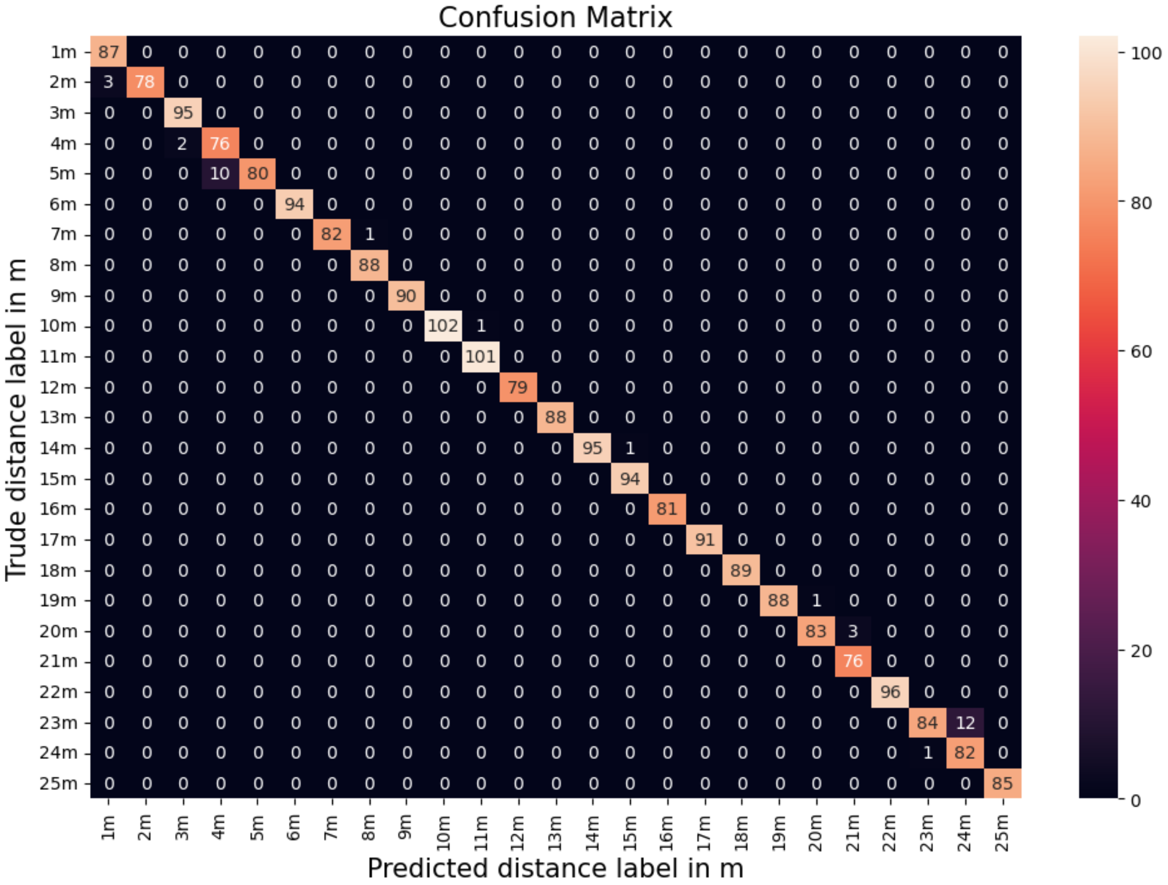
- Learning Loss and Accuracy using calibrated and filtered dataset.





Result and Analysis

- Accuracy of Range Estimation Model is 98.46%



	precision	recall	f1-score	support
1m	0.98	1.00	0.99	87
2m	1.00	0.98	0.99	81
3m	1.00	1.00	1.00	95
4m	1.00	0.96	0.98	78
5m	0.97	1.00	0.98	90
6m	1.00	1.00	1.00	94
7m	0.97	1.00	0.98	83
8m	1.00	0.97	0.98	88
9m	1.00	1.00	1.00	90
10m	0.99	0.99	0.99	103
11m	0.99	0.98	0.99	101
12m	1.00	1.00	1.00	79
13m	0.98	1.00	0.99	88
14m	1.00	0.99	0.99	96
15m	1.00	1.00	1.00	94
16m	1.00	1.00	1.00	81
17m	1.00	1.00	1.00	91
18m	1.00	1.00	1.00	89
19m	1.00	0.99	0.99	89
20m	0.99	0.98	0.98	86
21m	0.97	0.97	0.97	76
22m	0.98	1.00	0.99	96
23m	0.91	0.92	0.91	96
24m	0.90	0.89	0.90	83
25m	1.00	1.00	1.00	85
accuracy			0.98	2219
macro avg	0.98	0.98	0.98	2219
weighted avg	0.98	0.98	0.98	2219

Figure: Confusion Matrix and Classification Report

Result and Analysis

- Total RTT range error give the bes t fit to Gaussian distribution with 0.389 mean and 0.095 m^2 variance

- The calibrated data can be consid ered to obey a standard normal di stribution with Zero mean and 0.1 16 m^2 variance.

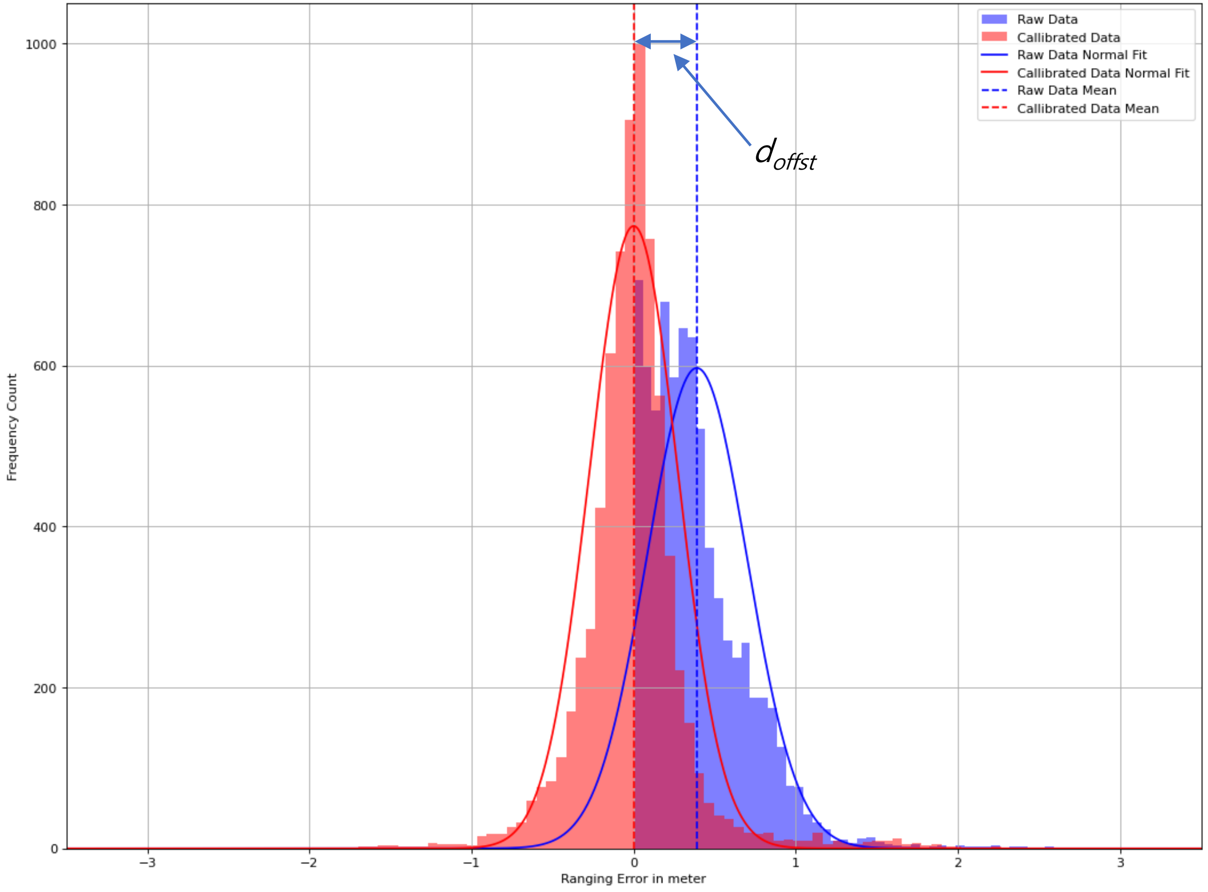


Figure: Comparison of range error between raw RTT and calibrated RTT

Result and Analysis

Features	Accuracy of model
Raw dataset only	86.97 %
Calibrated dataset only	94.14 %
Filtered & Calibrated dataset	98.46 %

Figure: Accuracy comparison based on features

- Accuracy can be calculated by: Accuracy=(TP+TN)/(TP+FP+TN+FN)
- We can see that using the Raw dataset and Calibrated dataset only , the accuracy is lower but with Kalman Filter we can predict with higher accuracy.
- Learning is better when data is calibrated with offset value and Kalman Filter.

Conclusion and Future Work

- Studied and proposed the Wi-Fi range estimation using a deep learning model for improved range estimation.
- To reduce the fluctuation of Wi-Fi FTM results, defined features in 802.11mc protocol and applied deep neural network.
- The evaluation results showed improved accuracy than conventional algorithms.
- If the trained data is not diverse enough, the model resulting from it can't be used for the generalized purpose, should have more data, and can approach the augmentation technique.
- In the future, plan to explore the research work by utilization of multiple access points and smartphones through more customized algorithms/models.
- Will explore and implementation of this model in multiple-floor localization.

References

- Guo, G., Chen, R., Ye, F., Peng, X., Liu, Z., & Pan, Y. (2019). Indoor Smartphone Localization: A Hybrid WiFi RTT-RSS Ranging Approach. *IEEE Access*, *7*, 176767–176781. https://doi.org/10.1109/ACCESS.2019.2957753
- Chigullapally, M., & Patnaik, S. (2020). Wi-Fi 802.11mc Distance Classification and Error Reduction using Machine Learning. *2020 5th International Conference on Communication and Electronics Systems (ICCES)*, 599–604. https://doi.org/10.1109/ICCES48766.2020.9137922
- Jung, B.-G., Chung, B. C., Yim, J., Yoo, Y.-S., & Park, H. (2021). Learning based Wi-Fi RTT Range Estimation. *2021 International Conference on Information and Communication Technology Convergence (ICTC)*, 1030–1032. https://doi.org/10.1109/ICTC52510.2021.9620218
- Dong, Y., Arslan, T., & Yang, Y. (2022). Real-Time NLOS/LOS Identification for Smartphone-Based Indoor Positioning Systems Using WiFi RTT and RSS. *IEEE Sensors Journal*, *22*(6), 5199–5209. https://doi.org/10.1109/JSEN.2021.3119234

Thank You