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## V406: Flood Forecasting using Edge AI and LoRa Mesh Network

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**Presenter: Mau-Luen THAM**



# I. Introduction

## Background

- Floods have been reported to be an important disaster in any country, resulting in disturbance in daily community routine issues, financial losses, infrastructure damage and the worst is the loss of lives.
- AI-based flood forecasting models have been researched in the hydrological engineering area for many years.
- The study in [2] applied artificial neural network (ANN) model to forecast river flow for 15 years starting from 2000.
- **Drawback:** Conventional ANN models have limitation of memory in calculating sequential data.

# I. Introduction

## Problem Statement

- Better accuracy can be accrued by utilizing deep neural network (DNN) models such as long short-term memory (LSTM) [3] and gated recurrent unit (GRU) [4].
- In an Internet of Things (IoT) environment, rainfall and river water levels can be collected at different hydrological stations.
- Edge computing can be introduced to process and analyze the valuable information from the raw sensor data at the network edge in real-time.
- Edge computing + artificial intelligence (AI) = **edge AI**.
- **Drawback:** The limited processing capacity constraints of IoT devices present a challenge to develop edge AI solutions.

## II. Related Work

### Edge AI

- The authors in [12] focused on real-time apple detection with the implementation of YOLOv3-tiny algorithm on low-power embedded platforms. However, the communication aspects were not considered.
- The authors in [6] proposed an edge AI in LoRa-based fall detection system with fog computing and LSTM. The processing burden is placed on an LoRa-based edge gateway, where the collected sensor information is transmitted from an edge node via Bluetooth Low Energy (BLE).
- **Drawback:** These works did not consider an effective IoT network connectivity. The transmission range of IoT sensor was limited by the BLE.

## II. Related Work

### IoT Network Connectivity

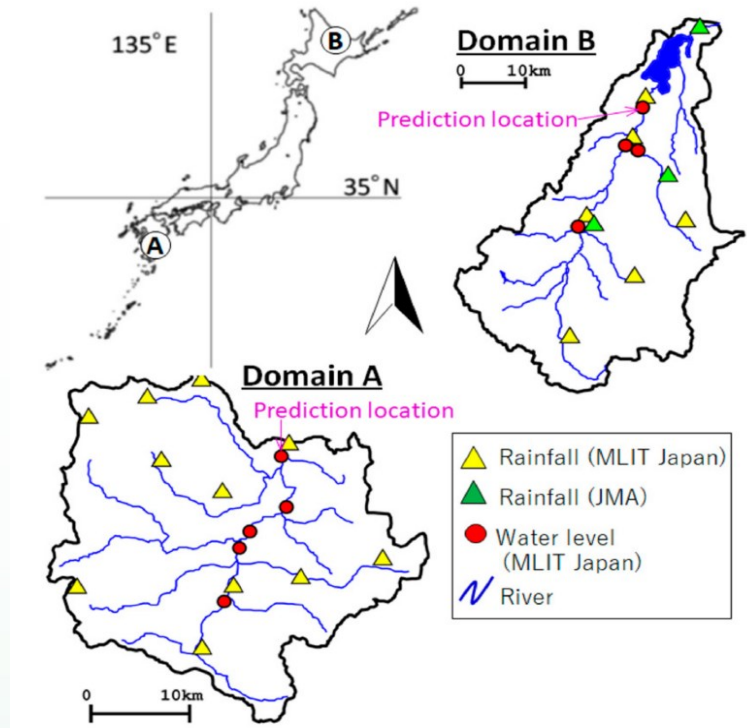
- To broaden the IoT coverage, the authors in [12] proposed a low-cost fine-grained air quality monitoring system using LoRaWAN. All LoRaWAN end devices distributed with average distance of 473m. However, edge AI was not considered.
- The authors in [13] developed AI enabled IoT sensing platform for real-time environmental monitoring. It enables ubiquitous protocols with short-range networks by offering BLE and WiFi connectivity and long-range network with LoRaWAN.
- **Drawback:** These networks are not suitable for broadcasting alert messages under disaster situations, where gateway could be damaged and could not forward the messages to remote server.

## II. Related Work

### Wireless Mesh Network

- Wireless mesh networks increase the resilience of a community because they create a redundant network of networks. Example are BATMAN and NerveNet.
- NerveNet is a specially developed mesh network for the regional area to provide reliable network access and a stable, resilient information-sharing platform in emergencies, even if the base station is destroyed in a disaster.
- We utilize NerveNet **LoRa mesh network** to increase the transmission range and reliability of edge AI-based flood monitoring solution.

### III. Dataset



Abashiri River watershed [8], located northeast of Hokkaido, Japan.

TABLE I. TRAINING AND TESTING PERIOD FOR THE DATASET

| Dataset                       | Training             | Test                 |
|-------------------------------|----------------------|----------------------|
| Hongou (Jan 2019 to Dec 2020) | Jan 2019 to May 2020 | Jun 2020 to Dec 2020 |

### III. AI Model Training

#### Google Colab (Intel® Xeon® CPU @ 2.20Ghz)

- Four types of AI models, namely Random Forest, SVM, LSTM and GRU.
- For Random Forest, the parameter 'max\_depth' represents each tree's depth in the forest. Here, we set the max\_depth value to 2.

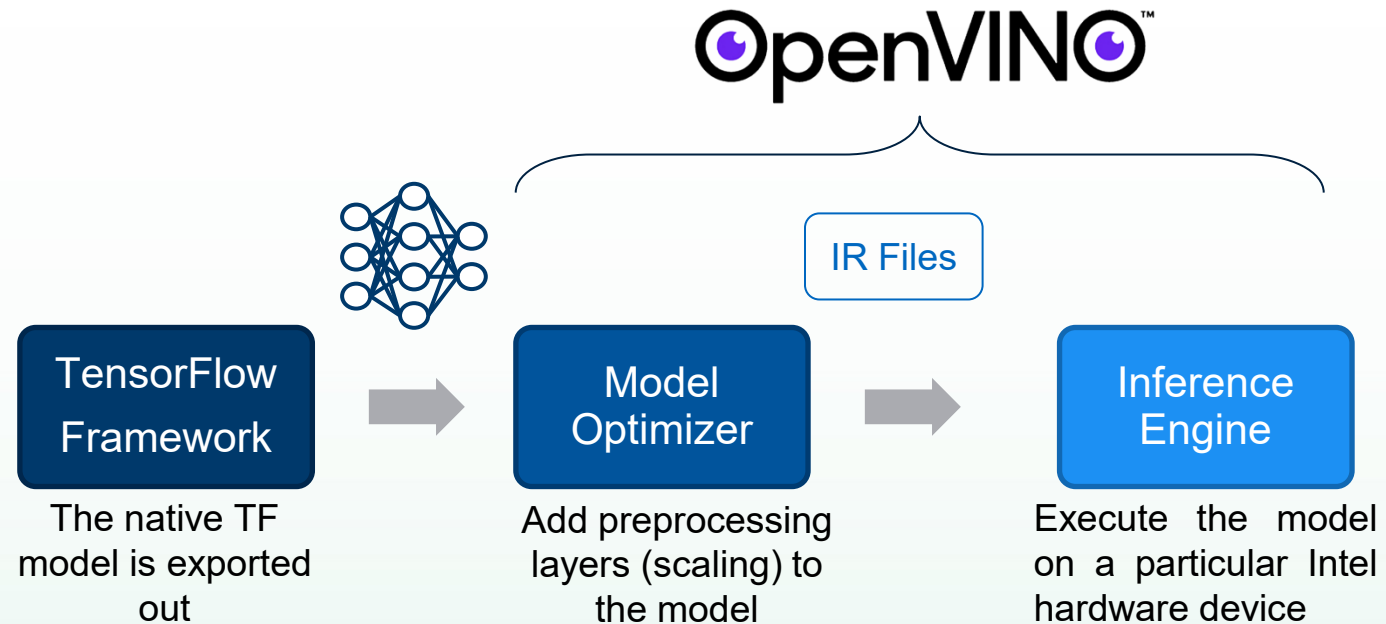
TABLE II. HYPERPARAMETER SETTINGS FOR LSTM MODEL.

| Hyperparameter         | Value                         |
|------------------------|-------------------------------|
| Sequence Length        | 24                            |
| Optimisation Algorithm | Root Mean Squared Propagation |
| Epoch                  | 50                            |
| Batch Size             | 64                            |



### III. AI Model Optimization

#### Open Visual Inference and Neural Network Optimization (OpenVINO)



### III. Edge AI Testbed

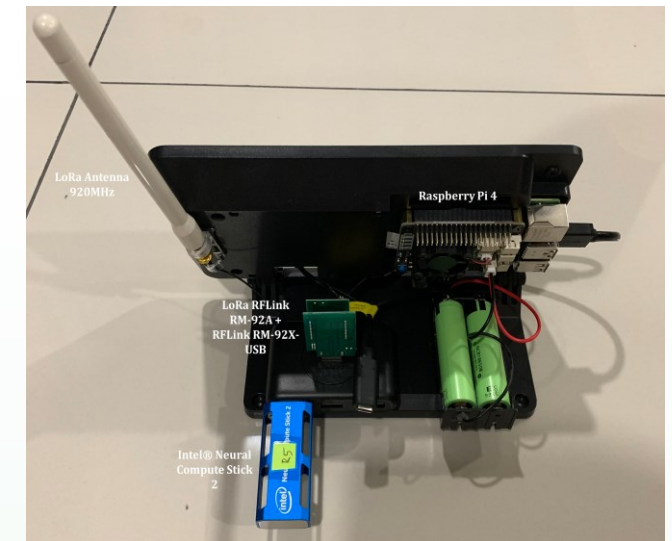
#### Message Queuing Telemetry Transport (MQTT): Publisher and Subscriber



(b)



(c)

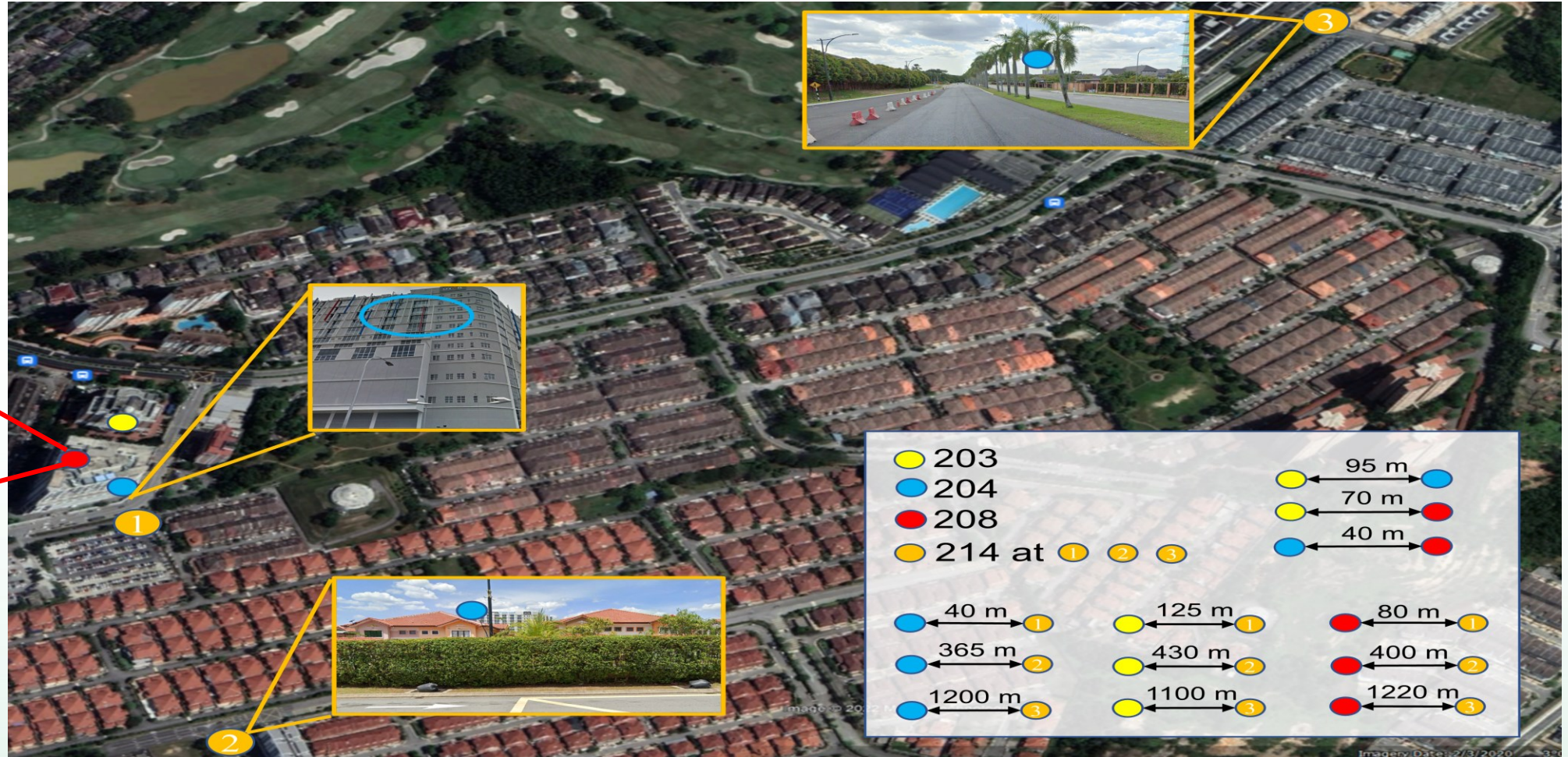


(d)

Fig. 2 Testbed. (b) Subscriber node (Intel NUC). (c) Publisher node (Raspberry Pi 4). (d) Publisher node (rear view).

## III. Edge AI Deployment

UTAR KB Block  
GPS coordinate  
(3.03960,  
101.79418)







### III. Edge AI Video Demo



## IV. PERFORMANCE EVALUATION (Prediction Accuracy)

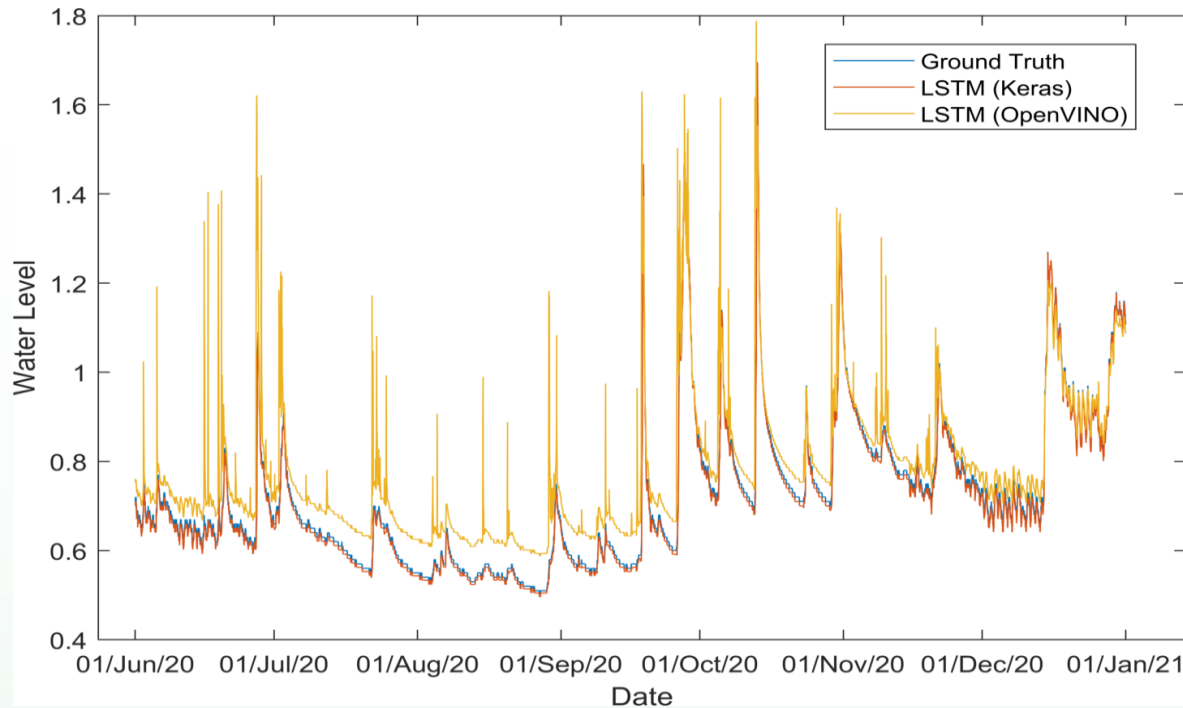
TABLE III. BENCHMARKING PERFORMANCE FOR PREDICTION

| AI Model        | MAE           | RMSE          | MAPE          | R <sup>2</sup> |
|-----------------|---------------|---------------|---------------|----------------|
| Random Forest   | 0.0656        | 0.078         | 0.0972        | 0.7807         |
| SVM             | 0.0541        | 0.0632        | 0.0763        | 0.8562         |
| GRU             | 0.0138        | 0.0154        | 0.0217        | 0.9915         |
| LSTM (Keras)    | <b>0.0088</b> | <b>0.0092</b> | <b>0.0126</b> | <b>0.997</b>   |
| LSTM (OpenVINO) | 0.0593        | 0.0907        | 0.0899        | 0.704          |

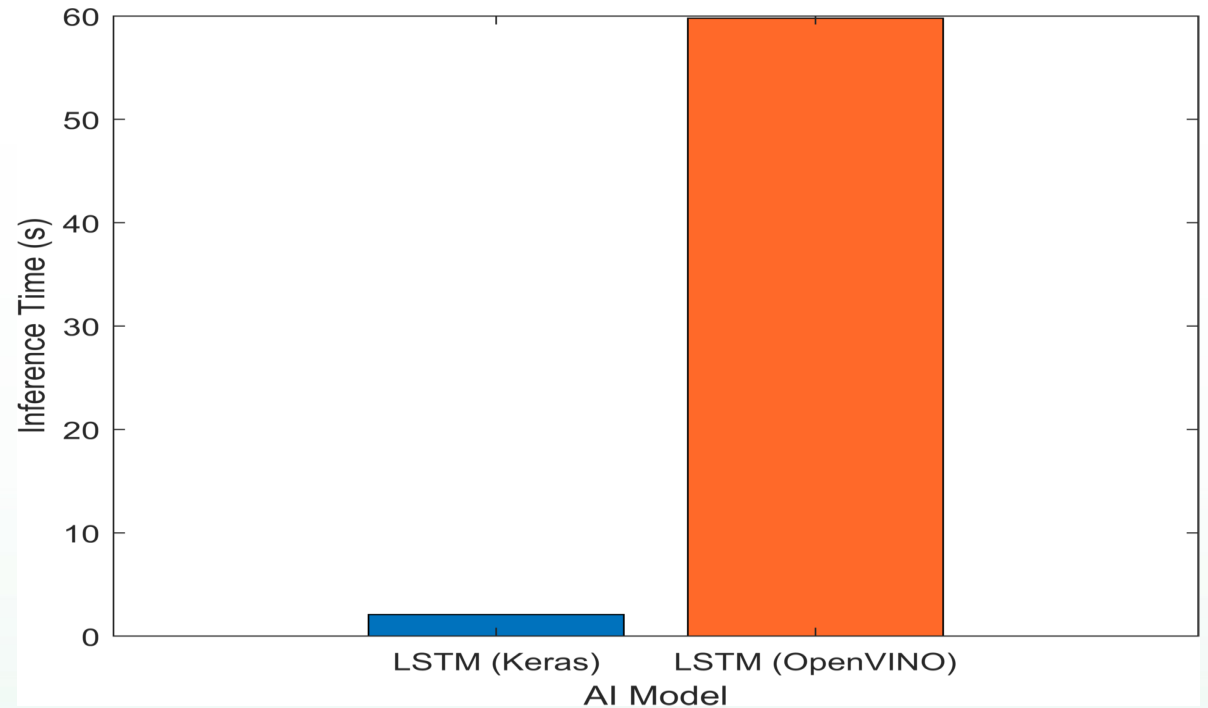
- mean absolute error (MAE) 
- mean absolute percentage error (MAPE) 
- root mean squared error (RMSE) 
- coefficient of determination and goodness of fit (R<sup>2</sup>) 



# IV. PERFORMANCE EVALUATION (LSTM Benchmarking)



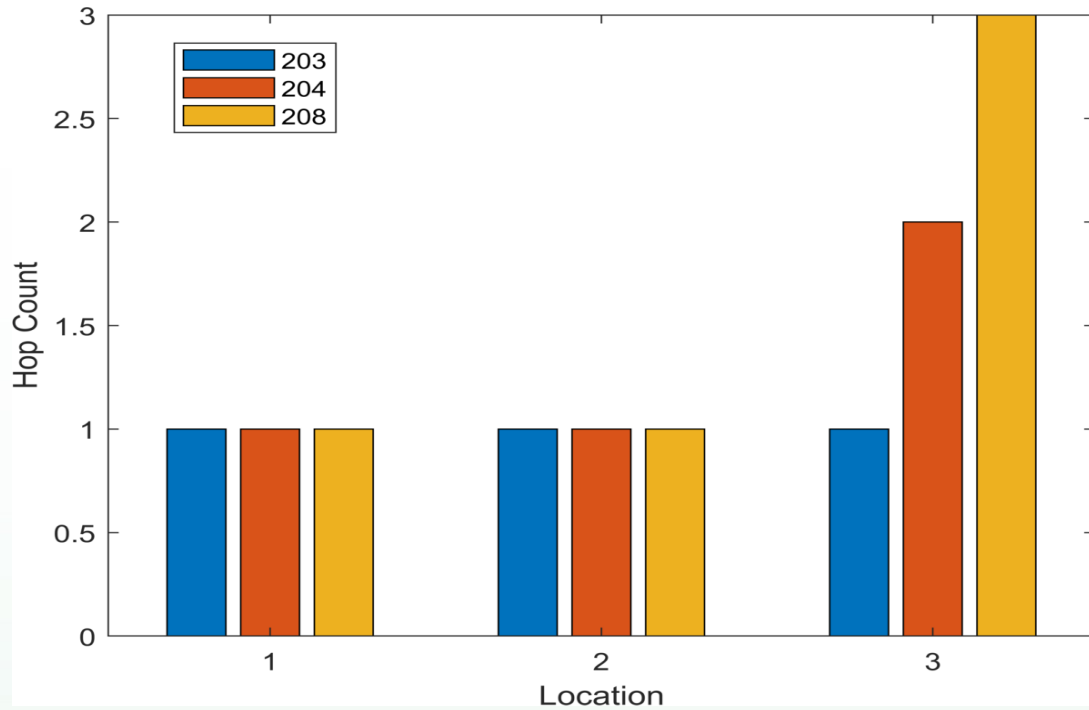
(a)



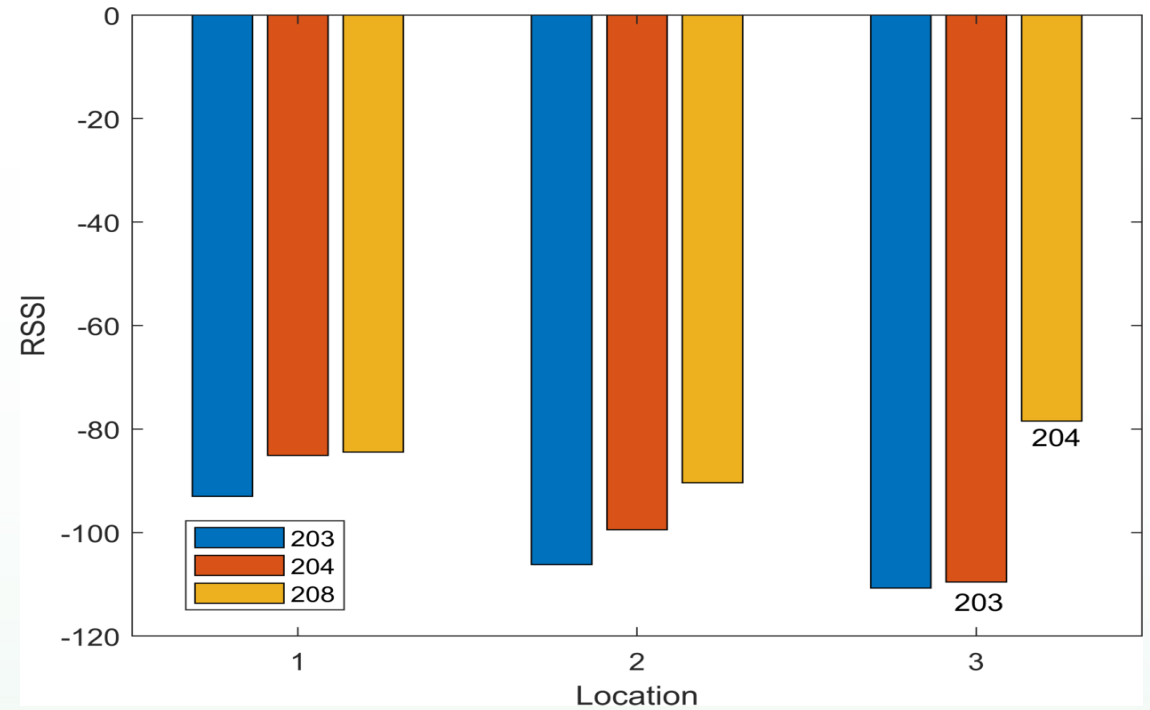
(b)

Fig. 1 LSTM performance benchmarking. (a) Prediction vs ground truth. (b) Inference time.

# IV. PERFORMANCE EVALUATION (LSTM Benchmarking)



(a)

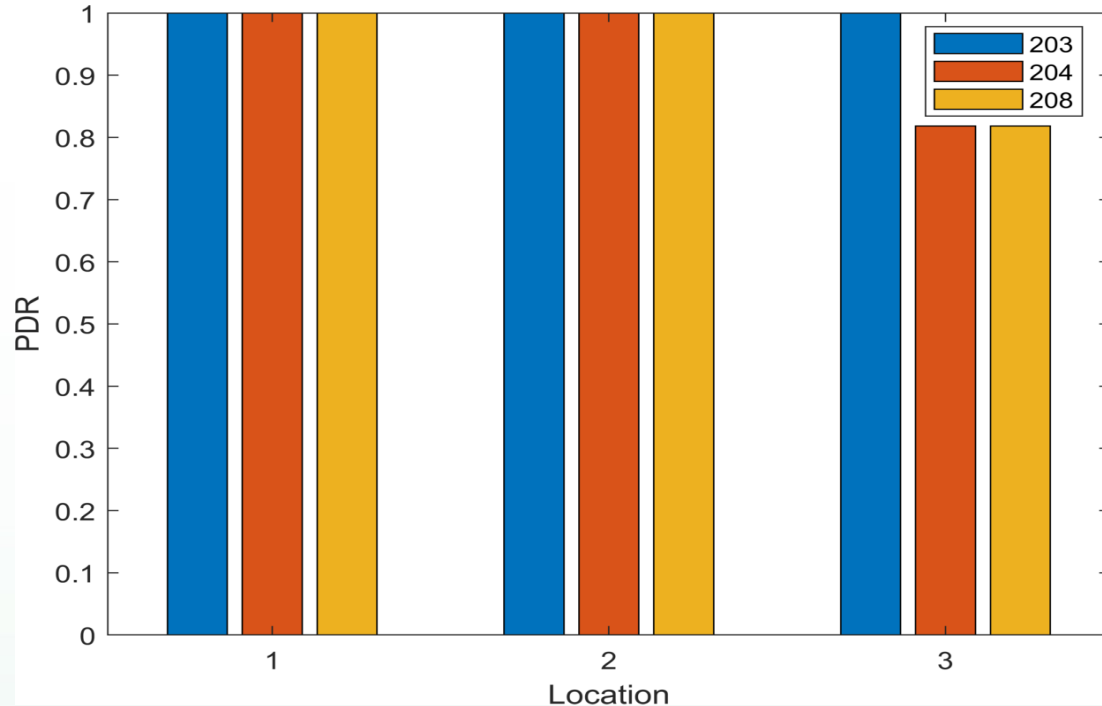


(b)

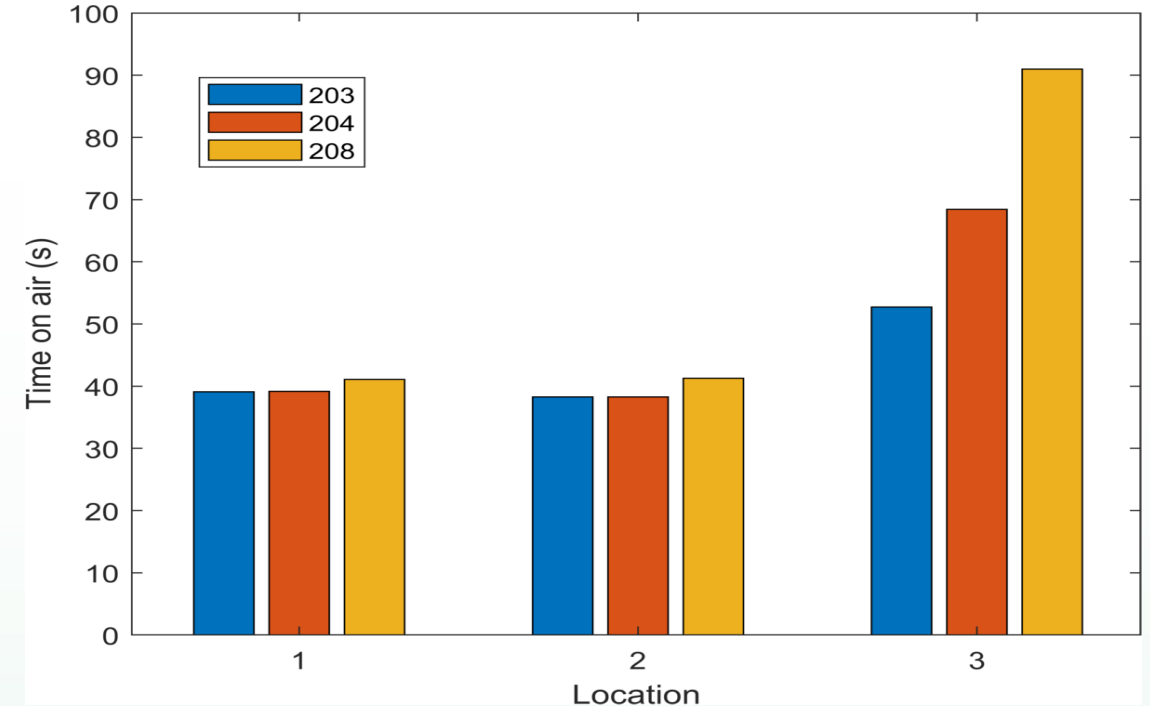
Fig. 3 Performance of NerveNet LoRaMesh. (a) Hop count. (b) RSSI.

# IV. PERFORMANCE EVALUATION (LSTM Benchmarking)

PDR=number of packets received /number of packets sent



(c)



(d)

Fig. 3 Performance of NerveNet LoRaMesh. (c) PDR. (d) Time on air.



## V. Conclusions

- In this paper, we have proposed an edge AI solution that forecasts flood water level and transmits the packet via LoRa mesh network.
- To reduce the heavy workload of AI inference, we utilized OpenVINO to accelerate the process so that it can be executed on low-powered Raspberry Pi device.
- The effectiveness of the solution has been demonstrated via a testbed implementation.
- In future, we plan to test the framework in a hybrid LoRa-Wi-Fi based mesh network.

