

ITU-ML5G-PS-016: LOCATION ESTIMATION USING RSSI OF WIRELESS LAN

Team Name:
SSN_ITU

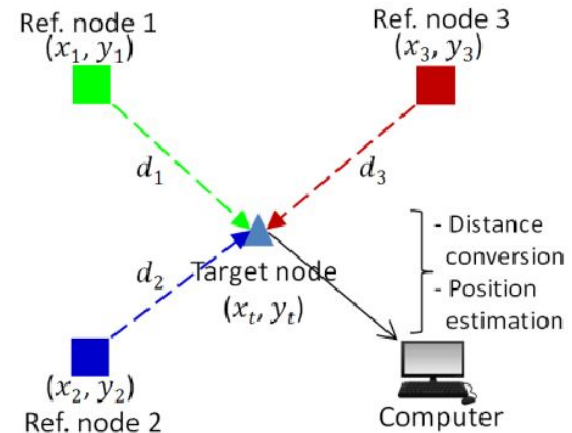
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N Venkateswaran

OBJECTIVE

1. To propose AI/ML aided localization, utilizing received signal strength indicator (RSSI) observed at the terminal with high accuracy as that of GPS-based localization.
2. Exploit the relationship between distance and RSSI
3. To find latitude and longitude of the nodes of a Wireless network

KEY ISSUES WITH RSSI

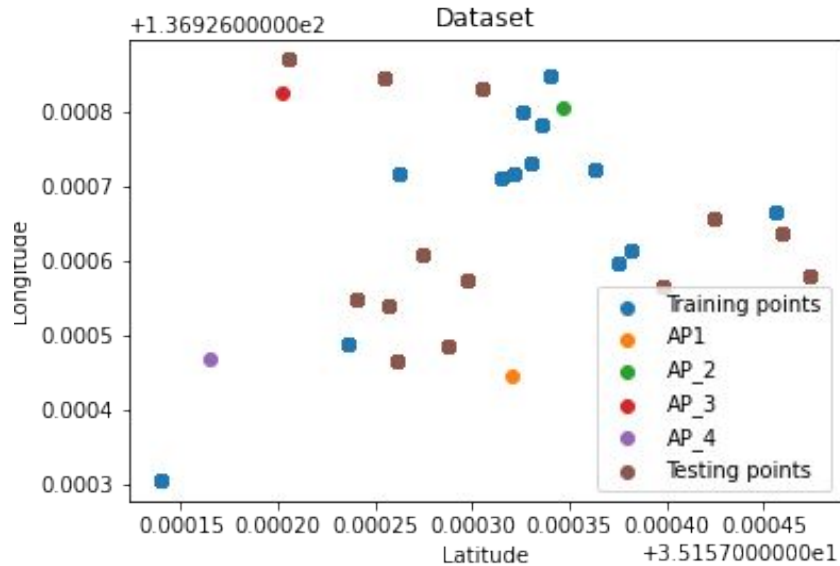
1. Highly prone to shadowing effects
2. Multipath fading affects the distance-RSSI relationship



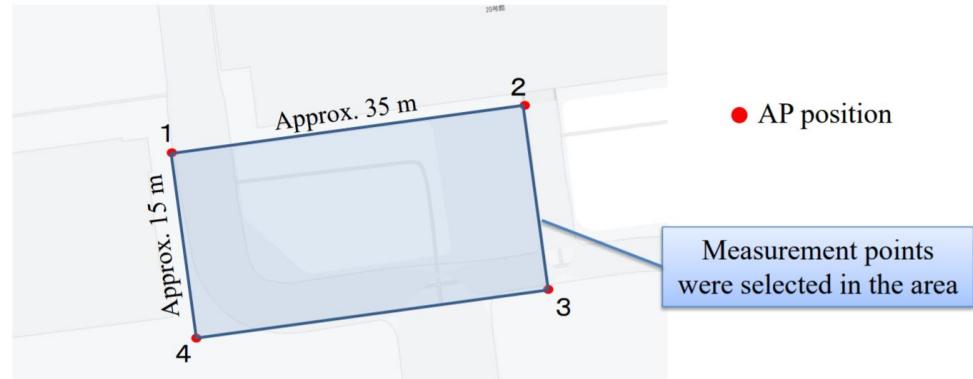


DATASET **ANALYSIS**

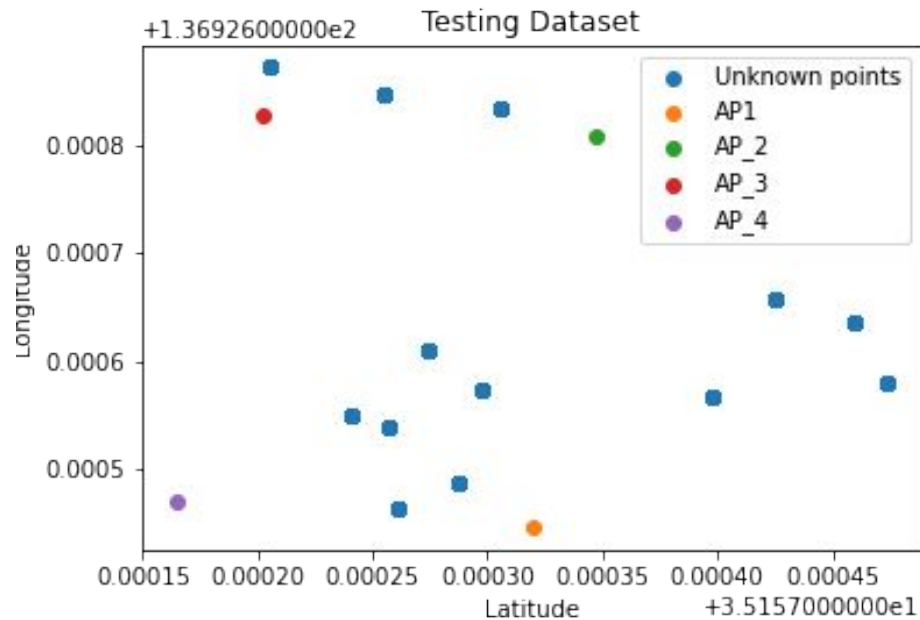
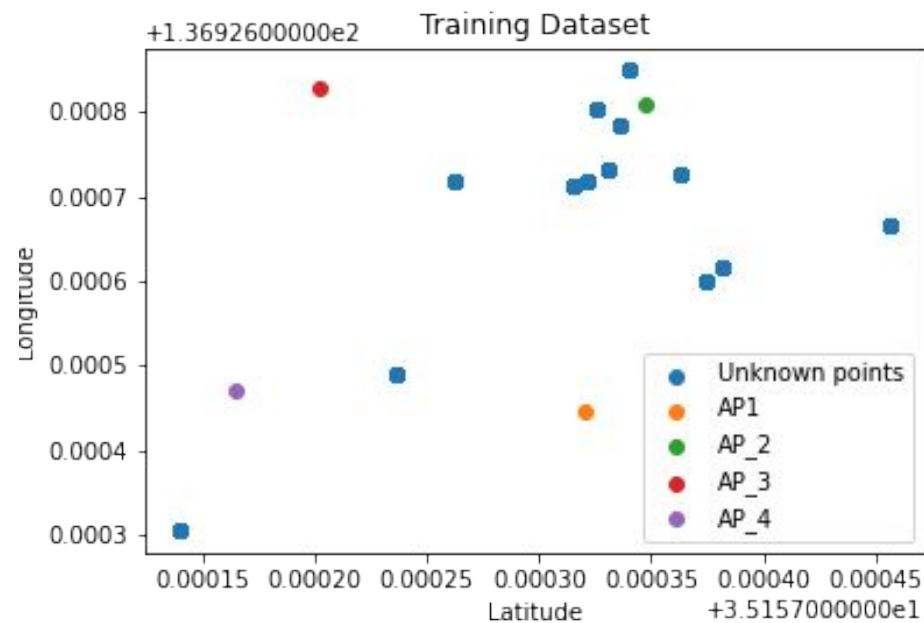
TOPOGRAPHY



- ① 4 access points (APs) were located at the location estimation area
- ② Locations of APs and measurement points were obtained by GPS
- ③ RSSIs were measured at each measurement point



VISUALISING POSITION OF DATA



INFORMATION GIVEN

- 4 Access Points
- 13 unknown nodes.
- Latitude, Longitude of APs
- Channel number of each AP
- Timestamps
- RSSI (dBm)

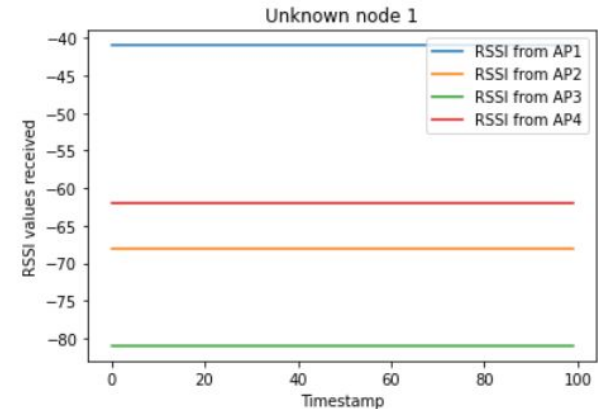
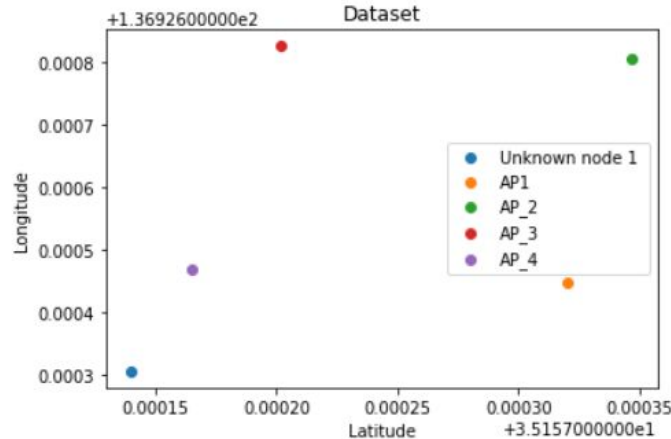
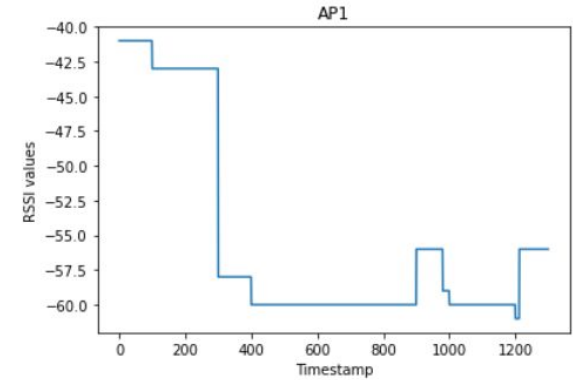
No.	TimeStamp(UNIX)	Latitude	Longitude	SSID	Channel	RSSI(dBm)	AP_x	AP_y
1	1631687696	35.157140	136.926306	1	11	-41	35.158465	136.924283
2	1631687697	35.157140	136.926306	1	11	-41	35.158465	136.924283
3	1631687697	35.157140	136.926306	1	11	-41	35.158465	136.924283
4	1631687697	35.157140	136.926306	1	11	-41	35.158465	136.924283
5	1631687697	35.157140	136.926306	1	11	-41	35.158465	136.924283
...
5196	1631688763	35.157236	136.926489	4	1	-52	35.158931	136.923835
5197	1631688763	35.157236	136.926489	4	1	-52	35.158931	136.923835
5198	1631688763	35.157236	136.926489	4	1	-52	35.158931	136.923835
5199	1631688763	35.157236	136.926489	4	1	-52	35.158931	136.923835
5200	1631688763	35.157236	136.926489	4	1	-52	35.158931	136.923835

AP SSID	Latitude	Longitude	Hight Difference(m)	Indoor/Outdoor
1	35.1573202	136.926447		0 Outdoor
2	35.157347	136.9268074		0 Outdoor
3	35.1572018	136.9268269		0 Outdoor
4	35.157165	136.9264698		0 Outdoor



DATASET **INFERENCE**

- Regression problem
- Sampling period is 100 sec for an unknown node from one AP, i.e an unknown node observes 100 RSSI values from one AP in this period.
- Does not always satisfy the distance-RSSI relationship
- RSSI values to multiple unknown nodes remain the same even though they are in different positions
- Less RSSI values (data points) for a complex environment
- Hence we need to model all these inconsistencies in the dataset



PROPOSED SOLUTION

LET'S CHECK OUT THE SOLUTION



TRAINING

BLOCK DIAGRAM

TRAIN
DATASET

5200 rows of training data
and 8 features
13 nodes

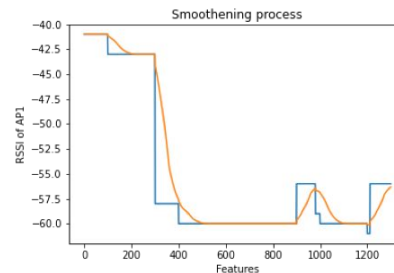
TimeStamp(UNIX)	Latitude	Longitude	SSID	Channel	RSSI(dBm)	AP_x	AP_y
1631687696	35.157140	136.926396	1	11	-41	35.158465	136.924283
1631687697	35.157140	136.926396	1	11	-41	35.158465	136.924283
1631687697	35.157140	136.926396	1	11	-41	35.158465	136.924283
1631687697	35.157140	136.926396	1	11	-41	35.158465	136.924283
1631687697	35.157140	136.926396	1	11	-41	35.158465	136.924283

DATA
RESTRUCTURING

1300 rows of training data
and 12 features

	AP_1	AP_2	AP_3	AP_4	AP1_x	AP1_y	AP2_x	AP2_y	AP3_x	AP3_y	AP4_x	AP4_y
0	-41	-68	-81	-62	35.158465	136.924283	35.158889	136.92435	35.15851	136.923762	35.158931	136.923835
1	-41	-68	-81	-62	35.158465	136.924283	35.158889	136.92435	35.15851	136.923762	35.158931	136.923835
2	-41	-68	-81	-62	35.158465	136.924283	35.158889	136.92435	35.15851	136.923762	35.158931	136.923835
3	-41	-68	-81	-62	35.158465	136.924283	35.158889	136.92435	35.15851	136.923762	35.158931	136.923835
4	-41	-68	-81	-62	35.158465	136.924283	35.158889	136.92435	35.15851	136.923762	35.158931	136.923835

DATA SMOOTHENING



FEATURE SELECTION

DATA AUGMENTATION

3,25,000 rows

LONGITUDE
EXTRA TREES
MODEL

LATITUDE
EXTRA TREES
MODEL

Training the models



TESTING **BLOCK DIAGRAM**

TEST
DATASET

DATA
RESTRUCTURING

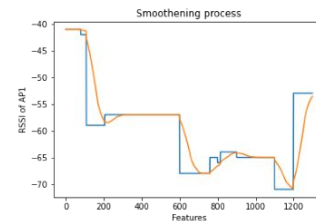
DATA SMOOTHENING

5200 rows of testing data
and 8 features
13 nodes

No.	TimeStamp(UNIX)	Latitude	Longitude	SSID	Channel	RSSI(dBm)	AP_x	AP_y
1	1631689137	35.157261	136.926465	1	11	-41	35.158465	136.924283
2	1631689137	35.157261	136.926465	1	11	-41	35.158465	136.924283
3	1631689138	35.157261	136.926465	1	11	-41	35.158465	136.924283
4	1631689138	35.157261	136.926465	1	11	-41	35.158465	136.924283
5	1631689138	35.157261	136.926465	1	11	-41	35.158465	136.924283

1300 rows of testing data
and 12 features

AP_1	AP_2	AP_3	AP_4	AP1_x	AP1_y	AP2_x	AP2_y	AP3_x	AP3_y	AP4_x	AP4_y
-41	-70	-73	-64	35.158465	136.924283	35.158889	136.92435	35.15851	136.923762	35.158931	136.923835
-41	-70	-73	-64	35.158465	136.924283	35.158889	136.92435	35.15851	136.923762	35.158931	136.923835
-41	-70	-73	-64	35.158465	136.924283	35.158889	136.92435	35.15851	136.923762	35.158931	136.923835
-41	-70	-73	-64	35.158465	136.924283	35.158889	136.92435	35.15851	136.923762	35.158931	136.923835
-41	-70	-73	-64	35.158465	136.924283	35.158889	136.92435	35.15851	136.923762	35.158931	136.923835



FEATURE SELECTION

LOCATION
OF
13 UNKNOWN
NODES

Latitude of 13
unknown nodes

LATITUDE
EXTRA TREES
MODEL

Longitude of 13
unknown nodes

LONGITUDE
EXTRA TREES
MODEL



DATA **PREPROCESSING STEPS**

01. DATA RESTRUCTURING

No.	TimeStamp(UNIX)	Latitude	Longitude	SSID	Channel	RSSI(dBm)	AP_x	AP_y
1	1631687696	35.157140	136.926306	1	11	-41	35.158465	136.924283
2	1631687697	35.157140	136.926306	1	11	-41	35.158465	136.924283
3	1631687697	35.157140	136.926306	1	11	-41	35.158465	136.924283
4	1631687697	35.157140	136.926306	1	11	-41	35.158465	136.924283
5	1631687697	35.157140	136.926306	1	11	-41	35.158465	136.924283
...
5196	1631688763	35.157236	136.926489	4	1	-52	35.158931	136.923835
5197	1631688763	35.157236	136.926489	4	1	-52	35.158931	136.923835
5198	1631688763	35.157236	136.926489	4	1	-52	35.158931	136.923835
5199	1631688763	35.157236	136.926489	4	1	-52	35.158931	136.923835
5200	1631688763	35.157236	136.926489	4	1	-52	35.158931	136.923835

ORIGINAL

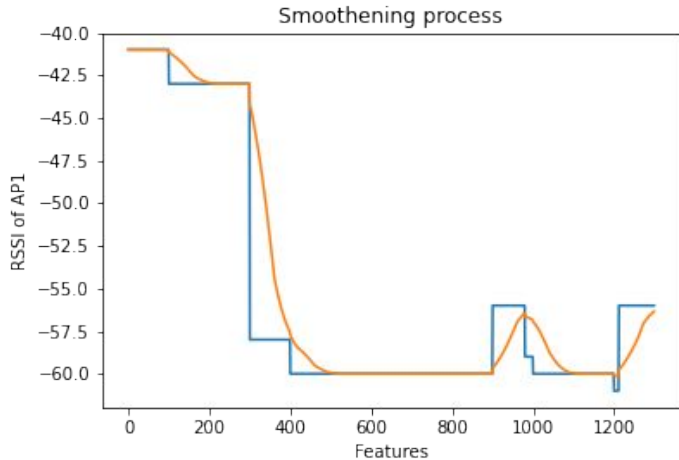
5200 rows with 8 features

	AP_1	AP_2	AP_3	AP_4	AP1_x	AP1_y	AP2_x	AP2_y	AP3_x	AP3_y	AP4_x	AP4_y
0	-41	-68	-81	-62	35.158465	136.924283	35.158889	136.92435	35.15851	136.923762	35.158931	136.923835
1	-41	-68	-81	-62	35.158465	136.924283	35.158889	136.92435	35.15851	136.923762	35.158931	136.923835
2	-41	-68	-81	-62	35.158465	136.924283	35.158889	136.92435	35.15851	136.923762	35.158931	136.923835
3	-41	-68	-81	-62	35.158465	136.924283	35.158889	136.92435	35.15851	136.923762	35.158931	136.923835
4	-41	-68	-81	-62	35.158465	136.924283	35.158889	136.92435	35.15851	136.923762	35.158931	136.923835
...
1295	-56	-70	-70	-52	35.158465	136.924283	35.158889	136.92435	35.15851	136.923762	35.158931	136.923835
1296	-56	-70	-70	-52	35.158465	136.924283	35.158889	136.92435	35.15851	136.923762	35.158931	136.923835
1297	-56	-70	-70	-52	35.158465	136.924283	35.158889	136.92435	35.15851	136.923762	35.158931	136.923835
1298	-56	-70	-70	-52	35.158465	136.924283	35.158889	136.92435	35.15851	136.923762	35.158931	136.923835
1299	-56	-70	-70	-52	35.158465	136.924283	35.158889	136.92435	35.15851	136.923762	35.158931	136.923835

AFTER RESTRUCTURING

1300 rows with 12 features

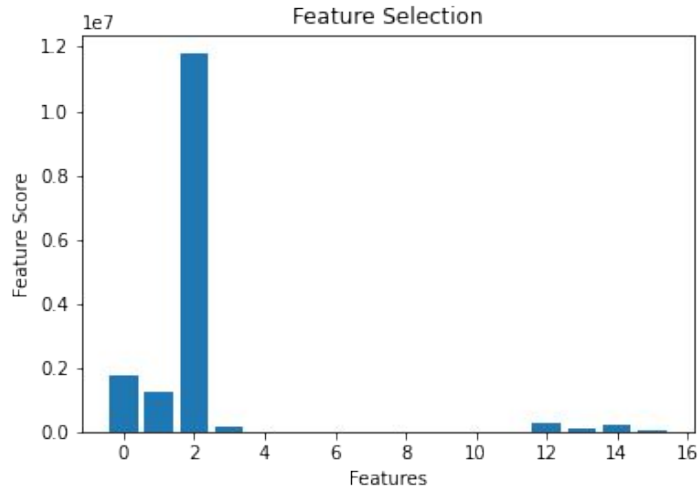
02. DATA SMOOTHENING



$$\text{CURR_VAL} = \text{CURR_VAL} * \alpha + (1 - \alpha) * \text{AVG_VAL}$$

- The RSSI values observed by the target nodes are highly dynamic. And in some cases, the RSSI values are similar for 2 or more target nodes, which hampers accurate learning process of the model.
- This in turn weighs down the accuracy of the model.
- Therefore, we formulated a data smoothing method called the windowing method.
- The process is to select a window size 'n' and to determine the average of these values. The weightage of this average value on the current RSSI values is determined by ' α '.

03. FEATURE SELECTION



FEATURE 7, 8 AND 9 ARE REMOVED

- Irrelevant or partially relevant features can negatively impact model performance.
- Having irrelevant features in your data can decrease the accuracy of the model.
- Hence we select only those features which contribute most to the output that we are interested in.

- Correlation is a measure of how 2 variables change together.

SelectKBest() from scikit-learn machine library uses correlation statistics to provide scores for all features

- The scores that are in the negative range or zero are neglected and the scores that fall under the positive range are considered.

04. DATA AUGMENTATION

- Technique that is used to increase the amount of data by adding copies of already existing data.
- The number of duplicates is determined by a factor “num”.
- For every unique target node, “num” number of duplicates are generated.
- Reduces the risk of overfitting and the accuracy on unseen data can be improved.

For the given data, we have used num=10000

- Shape of training dataset : (1300, 18)
- Shape of training dataset after augmenting: (130000, 18)



EXTRA TREES **REGRESSION MODEL**

EXTRA TREES REGRESSION MODEL

- The Extra Trees algorithm works by creating a large number of unpruned decision trees from the training dataset.
- Predictions are made by averaging the prediction of the decision trees in the case of regression.
- An ensemble method
- Provided by sklearn library

```
def extraTrees_LatModel(X_train, ytrain_lat):  
  
    extra_trees_regressor_lat = ExtraTreesRegressor()  
    extra_trees_regressor_lat.fit(X_train,ytrain_lat)  
  
    return extra_trees_regressor_lat
```

```
def extraTrees_LonModel(X_train, ytrain_lon):  
  
    extra_trees_regressor_lon = ExtraTreesRegressor()  
    extra_trees_regressor_lon.fit(X_train,ytrain_lon)  
  
    return extra_trees_regressor_lon
```

WHY REGRESSION MODEL

- Regression is a type of supervised learning task. It is used in cases where the value to be predicted is continuous.
- Regression is used to predict the value of the dependent variable for which some information concerning the explanatory variables is available, or in order to estimate the effect of some explanatory variable on the dependent variable.
- As we need to predict the Latitude and Longitude of the unknown node, given a set of dependent features, we have used **Regression**
- We have used **Extra Trees regression model** to model the given ITU Dataset

RESULTS

LET'S SEE HOW THE MODEL WORKS!

ERROR IN MODELS

```
Error in Predicting Latitude:  
Mean Absolute Error: 6.612467982780419e-05  
Mean Squared Error: 5.857772308461443e-09  
Root Mean Squared Error: 7.653608500871627e-05  
Maximum error: 0.00014949614640613618  
--- 1070.9163303375244 seconds ---
```

LATITUDE MODEL

```
Error in Predicting Longitude:  
Mean Absolute Error: 0.00010863203350197637  
Mean Squared Error: 1.568777933146181e-08  
Root Mean Squared Error: 0.0001252508655916669  
Maximum error: 0.00021503229709196603  
--- 1070.9327092170715 seconds ---
```

LONGITUDE MODEL

PERFORMANCE OF MODEL

Predicting Location:

```
Error of unknown loc 1 : 4.938806277573051
Error of unknown loc 2 : 17.64410609885038
Error of unknown loc 3 : 14.56878511151492
Error of unknown loc 4 : 11.265516993581313
Error of unknown loc 5 : 16.75676251593451
Error of unknown loc 6 : 9.345430964298226
Error of unknown loc 7 : 13.587220015745304
Error of unknown loc 8 : 16.462637949794836
Error of unknown loc 9 : 9.462216708598106
Error of unknown loc 10 : 17.54461631055337
Error of unknown loc 11 : 17.786571000997192
Error of unknown loc 12 : 18.320246462133195
Error of unknown loc 13 : 7.653023663509865
```

Maximum error in metres : 18.320246462133195

Average error in metres : 13.487380005621866

CONCLUSION

CONCLUSION

- On the given dataset, we have implemented the AI/ML model called **Extra Trees regression model**, to localise the unknown node in combination with some data-preprocessing techniques.
- The techniques included, data restructuring, data smoothening, feature selection and data augmentation.
- Used 2 models, one to predict the latitude and one for the longitude.
- Obtained a maximum error of 18.3m with an average error of 13.48m in a 35x15m field.

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THANK YOU



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