Deep Learning Indoor Localization Based on Wi-Fi RSS Dataset

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Abstract

Indoor localization is enabling numerous location-based technologies with the ubiquitous introduction of wireless systems and the increasing availability of smart devices.
WiFi fingerprinting has been one of the most practical approaches for localizing location-aware services covering the multi-story building with the existing radio maps. There are Many fingerprint-based localization algorithms, however are computation-intensive, relying heavily on both the offline training phase and the online localization process. Location fingerprinting via wireless network infrastructure using wireless access points and received signal strengths (RSS) is one of the most common and successful localization innovations in an indoor environment where no line-of-sight transmission from the global positioning system (GPS) is available. It can then approximate the location of a user/device by searching the closest match in a database among its RSS measurement and the fingerprints of specific locations.
We assess the proposed system on the UJIIndoorLoc dataset with many state-of-the-art approaches that achieve high accuracy by experimenting with different optimizers and activation functions utilizing batch normalization and parameter tuning.

Keywords: multi-building and multi-floor indoor localization; Wi-Fi fingerprinting; deep learning; neural networks; multi-label classification, WAP, RSS

1. Introduction

Location-based technology is an important part of the evolution of the 21st century. As location-based technology provides high-quality services. All sectors use localization features in one way or another without a particular type of system. Only a global positioning system (GPS) requires in the system. GPS is the mechanism to locate a user by utilizing their smart systems. The indoor localization is to cover a large building area such as a big shopping mall or a university campus where there are several multi-story buildings under the same administration. The localization technique examines the longitude and latitude of the user to point out the user location.

These techniques use WiFi fingerprinting for tracking system signals. However, it should be noted that the location fingerprinting technique does not require the installation of any new framework or the modification of existing devices, but it is based on the existing wireless infrastructure, which is its key benefit over alternative techniques. Present state-of-the-art Wi-Fi fingerprinting techniques presume a hierarchical approach to indoor localization, the building location, direction (e.g., sign or coordinates), and floor of the location are assumed to be one at a time.

One of the core problems in Wi-Fi fingerprinting is how to cope with random signal fluctuations, noise from multi-path impacts, and system and location dependency in RSS measurements. Unlike older techniques that rely on complex filtering and time-consuming parameter tuning particular to specific conditions, due to their parameter tuning and flexibility to a wider range of conditions with standard architectures and training algorithms, popular deep neural networks (DNNs) could provide desirable solutions for Wi-Fi fingerprinting.

This paper is the first to extend DNNs to multi-building and multi-floor indoor locations, making use of their hierarchical existence in classification. RSS determines the intensity of the signal that reaches the localization device's signal from a WAP. WAP is a device that includes Wi-Fi and Bluetooth which allows the wireless devices to form a connection between them. WAP determines that the signal is sufficient or not to form a connection. The DNN used in this paper corresponds to deep learning models such as Neural Network, CNN, LSTM, and Random Forest that access RSS as input.

The remaining portion of the paper is organized as follows: In Sec. 2, about localization, we discussed the related work performed in the field of Deep Learning. Sec 3 describes the issue of indoor localization in a large building complex, with its problems resulting from the presence of multi-story buildings, and proposes a DNN design for multi-building and multi-floor indoor locations. The experimental data used in this paper is discussed in Sec. 4. Sec. 5 contains experimental results for the efficiency of the proposed DNN-based multi-building and multi-floor indoor localization system. Sec. 6 concludes our work in this paper and recommends areas for further study.

2. Related work

In [1] the main research experiment is performed at Xi'an Jiao tong-Liverpool University (XJTLU) focused on deep neural network (DNNs) for hierarchical building/floor classification and WiFi fingerprinting for location estimation. This experiment is used as a baseline in a variety of projects and we have even used some of its features in our paper. In this paper the authors demonstrate a prototype DNN-based indoor localization method for location estimation using RSS. The structured models provide state-of-the-art performance with less scalability.

In [2] paper author research the use of DNNs for scalable classification and floor-level position estimation based on fingerprinting. This author uses a scalable DNN architecture for Multi-Building and Multi-Floor Indoor Localization. The models used here provide better efficiency for energy consumption implementation and lower complexity for mobile devices. They also use SAE for the reduction of the feed forward classifier and provide a space dimension for the multi-label classification.

[3] In this paper the authors suggest the use of DNN thus obtaining satisfactory results in order to significantly reduce the word-force pressure of localization system design. They demonstrate that stacked autoencoders enable the feature space to be reduced efficiently to achieve robust and reliable building/floor classification.

In [4], a four-layer DNN produces a coarse positioning approximation, which in turn is refined by a hidden Markov model (HMM)-based fine localizer to produce a final position estimate. In both indoor and outdoor settings, which are divided into hundreds of square grids, the performance of the proposed indoor localization system is assessed.

In [5], the authors investigate the use of deep belief networks (DBNs) for indoor localization with two distinct types of Restricted Boltzmann Machines and evaluate the output of their approaches using simulated data in heterogeneous mobile radio networks using ray-tracing techniques. The authors concentrate mainly on the localization of a single plane in both cases and do not take into account the hierarchical complexity of multi-building and multi-floor indoor localization.

On the other hand, in [6], for building classification, a DNN consisting of a stacked autoencoder (SAE) and a feedforward multi-class classifier is used. The hierarchical complexity of construction classification is also not taken into account in this work, as the classification is conducted over flattened, one-dimensional labels of merged building and floor identifiers. The estimate of the floor-level location is therefore not considered at all. In this regard, the study discussed in this paper is the first to apply DNNs to multi-building and multi-floor indoor localization, taking advantage of its hierarchical nature of classification, to the best of our understanding.

3. System Architecture

3.1. Deep Learning Models

Following are the Deep Learning models used in this experiment

3.1.1. Neural Network Model: The neural network is a computational learning system that uses a network of functions to understand and translate a data input of one form into the desired output, usually in another form.

There are various types of neural networks, but they all are made of the same components: neurons, functions, synapses, weights, and biases.

Models of neural network models are forecasting techniques focused on basic mathematical models of the brain. They enable complex, nonlinear relationships between the dependent variables and their predictors. By learning from examples, they can also approximate functions and dynamics.

3.1.2. Convolutional Neural Network model (CNN): A convolutional neural network, most widely used to interpret visual imagery, is a subset of deep neural networks. CNN's are regularized variants of multilayer perceptron. Multilayer perceptron usually means completely connected networks, such that, each neuron from one layer is connected to all neurons in the next layer. Compared to other image classification algorithms, CNN uses hardly any pre-processing. A CNN model can be assumed to be a combination of two components: the extraction part of the feature and the classification part.

3.1.3. Long-Short-Term Memory (LSTM): LSTM networks are a form of recurrent neural network capable of depending on sequence prediction issues to learn order. LSTM has feedback links, unlike normal feedforward neural networks. The two technological challenges that LSTMs solve are gradients withdrawing and gradients exploding, all related to how the network is trained. This model processes information that passes on data as it propagates forward.

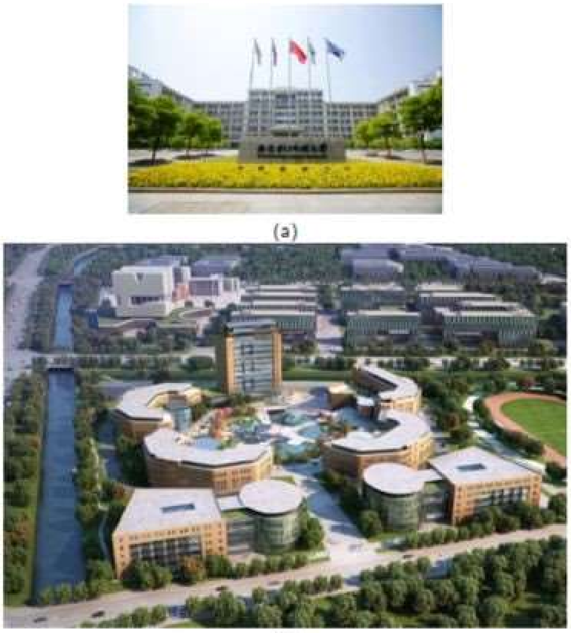
3.1.4. Random Forest (RF): This model creates and merges several decision trees to achieve a more precise and stable prediction. Random forests of decision making correct the practice of overfitting their training set for decision trees. The random forests model can be used to naturally identify the significance of variables in a regression or classification problem. Also, Random forests were an outstanding tool to learn representations of features.

3.2. Deep Learning Indoor Localization

Deep learning is a generalized form of machine learning methods based on artificial neural networks with language modeling (also known as deep structured learning). Learning may be controlled, sub, or uncontrolled. Essentially, deep learning is a class of algorithms of machine learning that uses several layers to gradually extract higher-level characteristics from the raw input. In this pandemic time, where work from home is central and necessary for less close interaction. Deep learning in Indoor location is used in this ongoing project for instance in [7] a deep learning approach is applied for non-contact COVID-19 detection through X-Ray images. This project used a deep learning algorithm for user tracking through blockchain. Whereas in [8] The dynamics of disease are evaluated by deep learning model and indoor localization

The ability to monitor without owning any WiFi devices is one critical aspect of the concealed potential of indoor localization. This means that if a device can detect nearby WiFi signals from nearby homes, it is possible to perform indoor localization using only the device. The way it works is to pinpoint the position of the user based on the signals that the user's device generates from the WiFi routers. Also, we can obtain the WAP's from multiple devices and execute indoor tracking. WAP and its related RSS values can be used to build deep learning models to predict the location of users with decent accuracy.

Consider the example [1] of the evolution of the Xi'an Jiao tong-Liverpool University (XJTLU) campus in Suzhou, China, where the authors are currently working, concerning indoor localization: As seen in Figure 1 (a), the XJTLU began with just one building in 2006. The XJTLU has two campuses as of this writing, which is seen in Figure 1 (b), and the number of buildings on two campuses has risen to about 20; as more buildings and sports facilities are being built, this number is also growing. The total number of different locations (e.g. offices, lecture rooms, and research labs) is now in the order of thousands, including all the floors inside each building and the locations on each floor.



(a) (b)

Figure 1: XJTLU campus in (a) 2006 and (b) 2020.

If we follow a grid-based representation of the localization region as in [4], the total number of locations will be much greater. The localization system indoors to occupy such a large complex of buildings. The task of classification of building/floor/location is divided into several sub-tasks dedicated to classification at each level of the building, floor, and location in the hierarchical architecture. This architecture is specifically consistent with state-of-the-art hierarchical methods of Wi-Fi fingerprinting (e.g.,[6]), where DNNs replace the conventional building, floor, and location estimation techniques.

A major disadvantage of this hierarchical DNN architecture is that different sub-datasets derived from a single dataset (i.e., building-specific datasets for floor estimation DNNs and building floor-specific datasets for DNNs for location estimation) need to be individually trained for the DNNs in the floor and device location levels comparison to the approaches based on traditional techniques. This presents significant challenges to preserving fingerprint location databases as well as planning possibly a sustained number of DNNs. Thus, the authors focus on the centralized architecture where a single DNN maintains the structure, floor, and position description for a common dataset in a systematic manner.

The number of nodes over the building complex is proportional to the number of locations: in the case of the UJIIndoorLoc dataset, the number of different locations over 3 buildings with 4 or 5 floors (also referred to as reference points in [9]) is 933.

To represent the hierarchical nature of the classification of building/floor/place in a DNN classifier, with the current multi-class classifier and flattened labels, one can use a hierarchical loss function, e.g., a loss function with different weights for building, floor, and position. The classification of building/floor/location with the proposed architecture is carried out as follows: First, building, floor, and location labels are mapped to sequential numbers, the latter two of which are only important in parallel with higher-level numbers; these numbers are individually encoded one-hot and combined into a vector as a categorical variable for multi-label classification as illustrated in Table 1. The output vector from the multi-label classifier is split by indexes into a building, a floor, and a position vector. Finally, via the arg max function, authors approximate the construction and the floor of a position as the index of the maximum value of the related vector. The above operation which takes place in XJTLU campus is referred in our paper.

In particular, in terms of computational complexity, the use of several elements in estimating position coordinates is a huge benefit because qualified DNNs with deep learning can produce multi-dimensional output values in parallel; on the other hand, in conventional methods, it is difficult and time-consuming to choose closest positions based on Euclidean distances. This versatility in managing DNN with deep learning localization outputs also makes it possible during the training process to add various weights to the cost of error in building, floor, and position classification

4. Experimental data

A large dataset that contains labeled positions and is publicly accessible is important to test proposed algorithms and facilitate comparison with methods proposed by other researchers.

We used the UJIIndoorLoc dataset in order to evaluate it with other approaches. This database contains three buildings, a number of locations, such as labs, offices. There are 520 columns from different WAPs. There are 24 devices in the selected dataset and 18 different users.

In the index, each scan contains 529 attributes.520 separate APs have been discovered in the area of operation, so the first 520 attributes tell about the signal intensity obtained from such networks. The signal intensity ranges from -104 dBm to almost 0 dBm in the event of bad reception. The value of 100 is given if AP is not available. The remaining 9 attributes include calculation longitude and latitude detail, floor number, building ID, room ID, relative location, user ID, telephone ID, and measurement timestamp. The dataset for UJIIndoorLoc consists of a sequence of user measurements.

In the UJIIndoorLoc dataset, four identifiers, i.e., Building ID, Floor, SpaceID, and RELATIVE POSITION, uniquely define the position of a place. We merge the SpaceID and the RELATIVE POSITION into one for simplicity and list it as a location in the paper so that the three house, floor, and location identifiers decide a location's position uniquely.[6] Slight variations occur between the UJIIndoorLoc dataset statistics mentioned in [3] and those of the UCI Machine Learning Repository publicly accessible dataset.

5. Experimental Evaluation

When the data is correctly pre-processed, it is eligible for training and processing. This is the time where all the models of deep learning shine. Numerous deep learning models can be used in multiple hyperparameter combinations. We used deep learning models such as Deep Neural Networks, Convolutional Neural Networks, LSTMs, and Random Forests.

With the use of the confusion matrix and the Receiver Operating Characteristic (ROC), we have defined the plotting function. Confusion matrix Also known as error matrix defines a particular table that enables the output of an algorithm to be visualized. The ROC curve is a graphical plot that indicates the diagonal ability of the outcome, in this case it shows the desired output for models concerning training and testing data. These data are enclosed with predictions and expected output. Data Pre-Processing contains the data types used in the dataset provided, Space distribution, and Feature Importance.

In the Figure 2 feature, importance is processed with WAP data in the dataset. This Feature importance is mapped with the help of a classification task that uses informative features from all the data. There are a total of 529 features normalized, but only a few are seen here since the graph was too long to fit into this report frame.

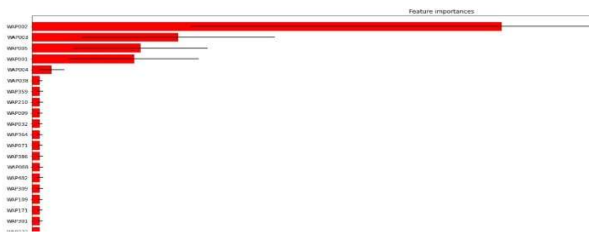


Figure 2: Feature importance plot.

After normalization of the featured data, the dataset is divided into two parts train and test data with training set-70 % and Testing set-30 % of the dataset. We build a total of three predictions and finally predicting building as a result of the experiment. For each scheme, we implemented four deep learning models with predictions.

5.1. Predicting Latitude and Longitude (LAT)

The first operation performed on this data is Predicting Latitude and Longitude (LAT). In this the neural network model specifies a batch size of 1024 and epochs of 150. The layer used in this is stated in Table 1 and Figure 5.

Table 1: Layers used for Neural Network model

Layers	Parameters	Filters
Dense	300	Relu
BatchNormalization	n/a	n/a
Dropout	0.2	n/a
Dense	150	Relu
BatchNormalization	n/a	n/a
Dropout	0.2	n/a
Dense	150	Relu
BatchNormalization	n/a	n/a
Dense	2	Linear

The raw data accuracy was 83% but using this model the accuracy obtain for normalized data is 97.91%. This situation is visualized in **Figure 3** and Figure 4.

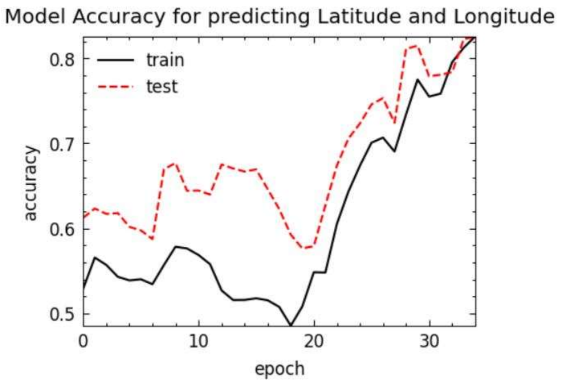


Figure 3. Validation of Latitude and Longitude using Raw Data.

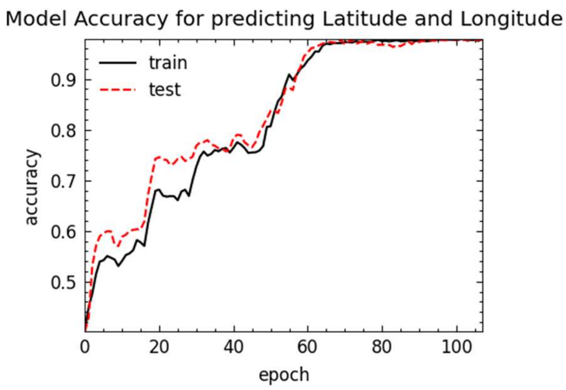


Figure 4. Validation of Latitude and Longitude using Normalized Data.

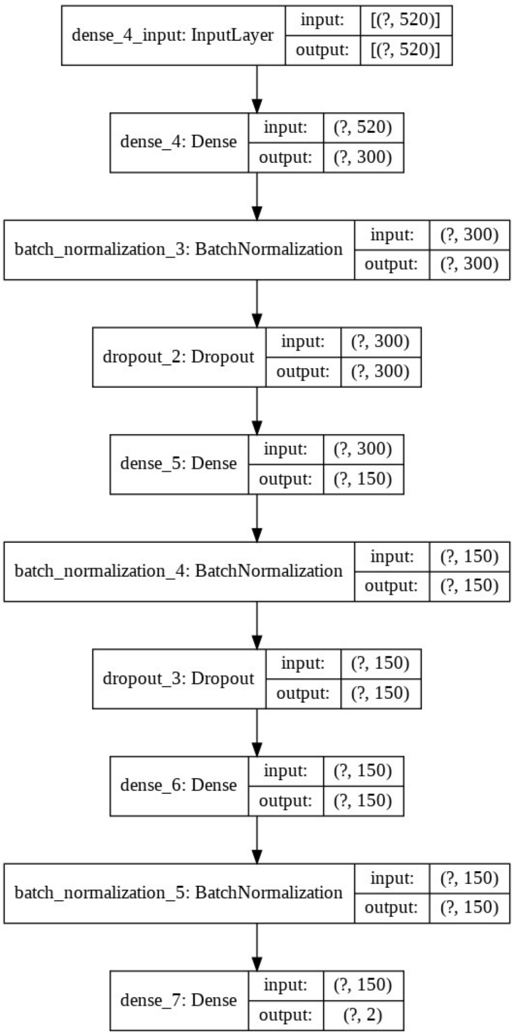


Figure 5. Framework of Neural Network model for Predicting Latitude and Longitude.

The second model is the CNN model and, in this model, the accuracy drop to 60.58%. The data and layer used in this model are defined in Figure 6 and Table 2.

Table 2.: Layers used for CNN model

Layers	Neurons	Kernel	Strides	Padding
Conv2D	64	(1,5)	(1,1)	same
Dense	300	n/a	n/a	n/a
Dense	150	n/a	n/a	n/a
Dense	150	n/a	n/a	n/a
Dense	2	n/a	n/a	n/a

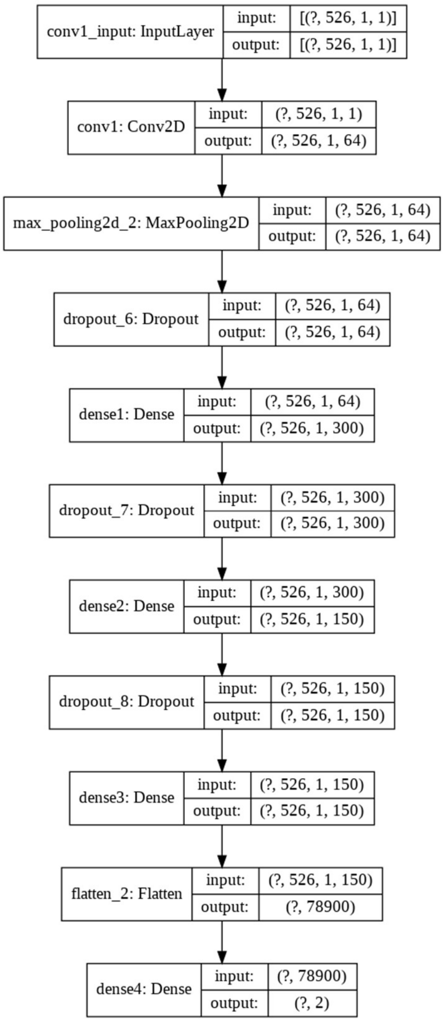


Figure 6. Framework of CNN model for Predicting Latitude and Longitude.

In this two-model method are used with a batch size of 1024 and epochs of 100.

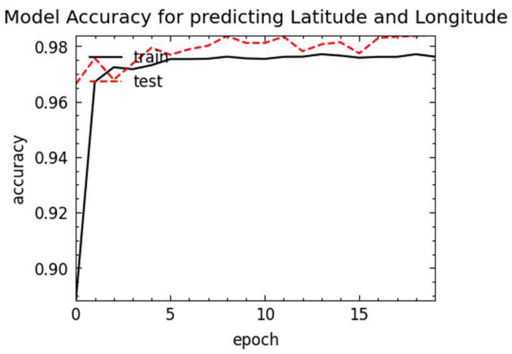


Figure 7. Predicting Latitude and Longitude using CNN model.

The Figure 7 and Figure 8 is the best of this model

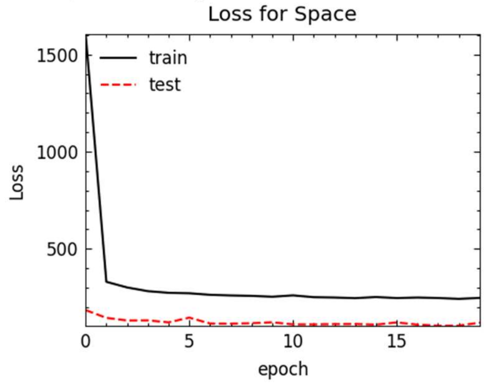


Figure 8. Predicting Latitude and Longitude Space Loss using CNN model.

Whereas in LSTM (Long short-term memory) accuracy reach up to 62.26 %. With the following layer defined in Figure 9 and Table **3**.

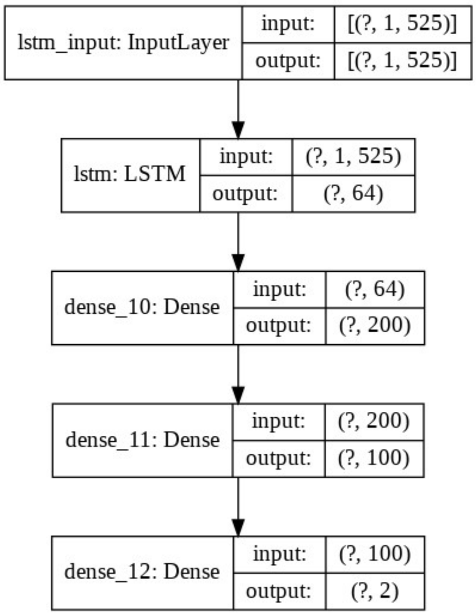


Figure 9. Framework of LSTM model for Predicting Latitude and Longitude.

Table 3. Layers used for LSTM model

Layers	Neurons	Filters
LSTM	64	Relu
Dense	200	n/a
Dense	100	n/a
Dense	2	n/a

Lastly Random Forest results accuracy of 97.63 %. Which is best accuracy among all other model in this section.

5.2. Predicting Space

The Predicting Space accuracy is the lowest among all other predictions. The accuracy of the models are as follows: NN- 58.79%, CNN- 63.36%, LSTM- 01.19% and RF- 56.97%. The best-case accuracy of the section is provided by the CNN model shown in Figure 10 and Figure 11 .

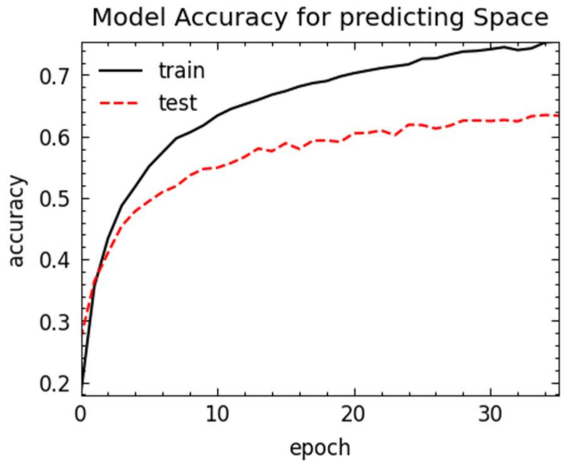


Figure 10. Predicting space accuracy by CNN model

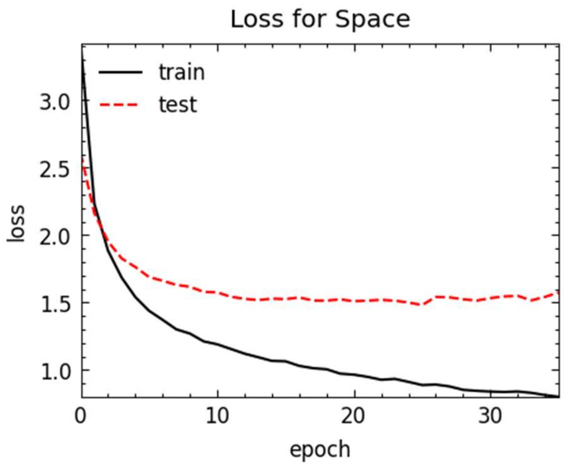


Figure 11. Predicting Space Loss using CNN model

The challenge of predicting space was substantially greater because the one-dimensional function had high redundancy, which made the training more challenging.

Whereas for latitude and longitude, due to the variation, there was a larger variance for the model to provide improved learning.

5.3. Predicting Relative Position

The relative location has only two values in which the model could think about the variations of WAP's with only two relative positions, which increased the efficiency of the training and testing.

All the prediction in this is better than previous. In NN model the accuracy occurs is 94.43% shown in Figure 12 and Figure 13 with batch size of 700 and epochs of 1000.

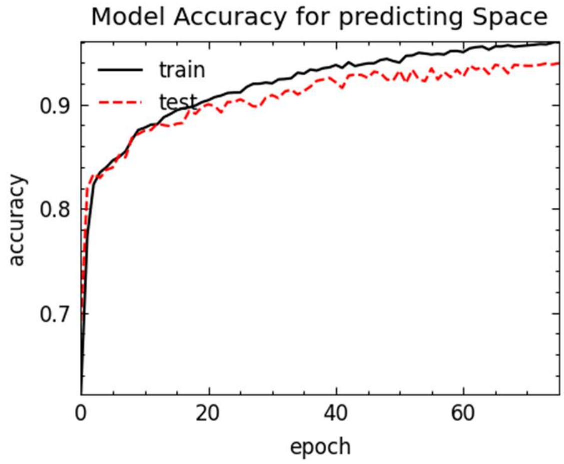


Figure 12. Predicting Relative Space using NN model

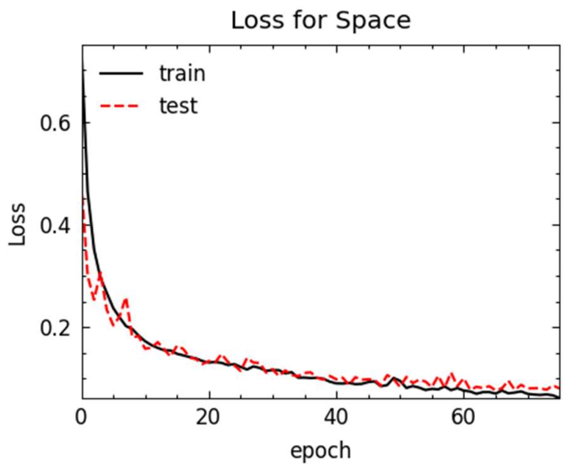


Figure 13. Predicting Relative Position space loss in NN model

The CNN model accuracy is 91.37% that is less than the NN model. In this batch size is 1000 and epochs are 400. The worst accuracy model in this section is LSTM which is 44.70%. Figure 14 shows that in detailed.

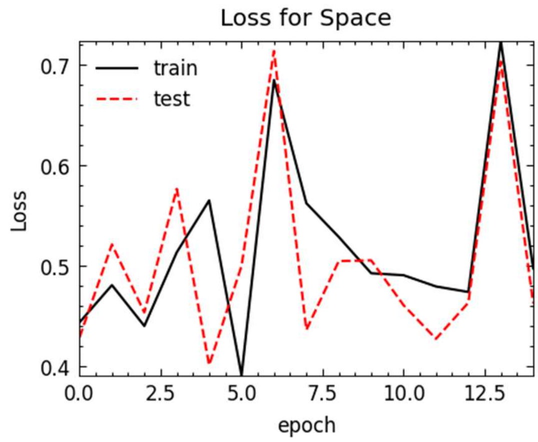


Figure 14. Loss of Relative position using LSTM model.

The best accuracy model so far in this project is obtained by RF. This model gives an accuracy of 97.36% which further improved in the final portion of this experiment.

5.4. Predicting Building

By the batch size 900 and epochs 100, finally in predicting buildings the location is identified with the help of precise model by the **accuracy of 99.94%.** Figure 5 and Figure shows the ideal output of this experiment.

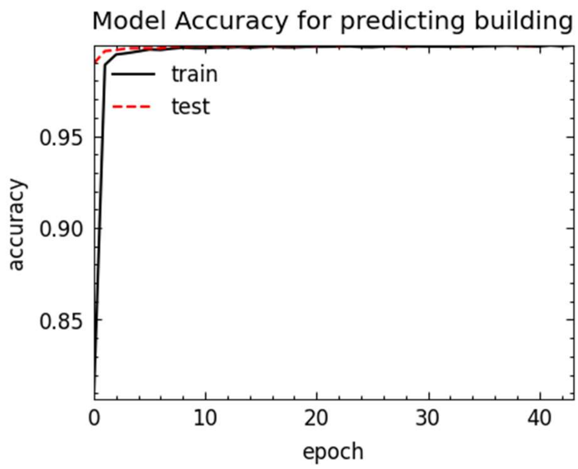


Figure 15. Predicting Building accuracy

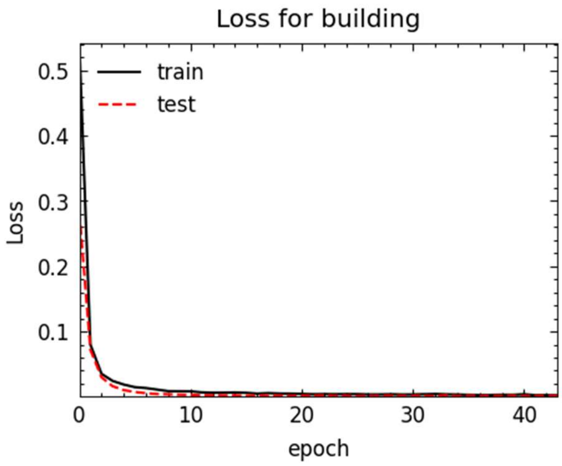


Figure 16. Loss of Data

Table 4. Overall Performance of Models

Models	NN	CNN	LSTM	RF
Latitude and Longitude	97.91%	60.58%	06.26%	97.63%
Space	58.79%	63.36%	01.195%	56.97%
Relative position	94.43%	91.37%	44.70%	96.53%

Table 5. Best and Worst accuracy models of three predictions

Predictions	Best Accuracy Model	Worst Accuracy Model
Latitude and Longitude	NN	CNN
Space	CNN	LSTM
Relative position	RF	LSTM

6. Conclusion

We also put in place a predictive system to predict the user's latitude and longitude when WAP RSS values are given. In addition, we have put together two more frameworks for forecasting space and relative. A user's place. Indoor localization has huge growth potential for a variety of applications. Indoor monitoring can support a range of large-scale sectors, such as hospitals, hospitality, and emergency services. Although the viability of applying this model is inexpensive, it should not be difficult to execute on a large scale. The use of this technology in smart IoT systems will lead to infinite possibilities in terms of what activities can be accomplished. We expect the companies that use motion capture and monitoring systems will make substantial profits. As part of the future work, we would like to use adversarial networks to create a new dataset by inputting the current dataset.

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