# Prediction of Indoor Wireless Coverage from 3D Floor Plans Using Deep Convolutional Neural Networks

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***Abstract*—With significant advancements in Machine Learning and Deep Learning, Convolutional Neural Networks (CNNs) have shown promising results in handling classification and regression problems. We present 3DRSSNet, a model that can predict the signal strength of an Access point in a 3-D environment based on the 3-D floor map of the building. Our deep CNN approach differs from previous work in that (i) it can generalize to unseen environments, and (ii) to the best of our knowledge, it is the first work to utilize 3D maps to build a signal strength prediction model and validate its results using actual measured data. The proposed neural network model can help solve problems lie optimal access point placement and blind spot detection. Experimental results show that CNNs can predict indoor radio link quality with a performance with a Mean Absolute Error of 4.4 dBm and is able to generalize well to unseen environments.**

***Index Terms*—Deep Learning, Radio Link Quality, RSS, Indoor Path Loss, Data Packets, Floor Plans, Neural Networks, CNN, Regression,**

## I. Introduction

Ensuring a stable and reliable platform for communication is one of a wireless network's most crucial roles. The network's ability to provide this platform for use is directly linked to the estimation of its radio link quality. The radio link quality estimation in wireless networks plays a fundamental role in designing its higher-layered protocols and directly relates to the network's performance. Learning ways to estimate and optimize the link quality and make correct spatial predictions of the value is vital for some wireless network protocols and applications.

In wireless networks, link quality is generally estimated by measuring Received Signal Strength (RSS). Several radio wave propagation phenomena such as diffraction, scattering, transmission, refraction, and reflection, have an effect on the RSS. Furthermore, in the majority of circumstances, the transmitter and the receiver are not in direct line-of-sight As a result, the RSS varies in time and location with regard to the receiver and transmitter [1]. The complex interplay among all these factors make precise link quality prediction a challenging task in wireless networks. This problem is exacerbated in indoor wireless networks because the involvement of the environment (e.g., walls, ceilings) in determining signal strength at a given place is difficult to compute [2], [3].

Given the growing importance of predicting the RSS values and the task's complexity to take into account multiple variables, we propose, 3DRSSNet, a novel neural network architecture for indoor radio link quality estimation by predicting the Received Signal Strength (RSS) value that differs in two critical aspects compared to most existing DL approaches. Firstly, it considers the complete 3D structure of the surrounding, accounting for all the objects and other obstacles, predicting scattering and blockage of the signal by the obstacles. Secondly, it predicts the value independently of the location of the access point and the receiver. The model is built on the idea that the surrounding environmental elements play a vital role in determining the signal strength at a location. It uses a regressive Convolution Neural Network (CNN) approach that responds very well to the importance of adjacent measurement in a 3D topology. CNNs are considered "universal function approximators", which allows them to learn the relationships between 3D objects, signal strength measurements, and the signal strength field [4].

## II. Related Work

Existing related works on radio link quality prediction in general differ in the assumptions made, the scenarios of experimentation, and the methods employed. It was noted that the results produced were radically different, sometimes even contradictory. Another difference is the metric monitored, e.g., RSS [5], Packet Reception Rate (PRR) [6], among others.

Different approaches have been used to predict wireless link quality. Some works aim to create mathematical models to approximate the physical aspects of the wireless propagation [7]. These models rely on numeric data that is backed by physics as their basis for model creation. Other works aim to create models using intelligent algorithms such as machine learning and deep learning tools to learn features and estimate the link quality [8], [1], [9], [10], [11]. These works are more data-driven in the context of information and aim at detecting and learning from features of the provided data.

The selection of data to train the models and the prediction target can play a crucial role in determining the performance and accuracy of the model. From attempted known works, it becomes apparent that models which rely on classification tend to underperform as they cannot predict the values but only classify them over ranges. Regression-based models are trained with numeric data from simulations (e.g., [11]), but and also tend to underperform as they fail to consider the impact of the surrounding environment of the wireless network. This raises the need for a regressive model with considerations for environmental and other numeric factors.

Easy accessibility to 2D environmental representations (like satellite images [12], and city-maps [11]) prompts most works to rely on them as inputs. However, the use of 2D data can significantly limit the information about a structure. Other approaches combine interpolation techniques with machine learning models to estimate radio spectrum metrics [10]. These approaches require data to be collected from the same environment where the predictions are made.

We propose a novel approach to learn the factors that affect radio link quality in wireless signals. Our research attempts to address some of the previously stated omissions and presents a new approach to predict link quality by recording the RSS value while considering the multilayered floor plan of the structure. We let the model detect and understand features more explicitly by providing the 3D floor plan with three information channels.

With such assisted training, the model can learn to predict the signal strength with a manageable loss factor and develop practical generalization capabilities.

## III. Prediction Model

We use a deep learning model to capture the relationship between the 3D map of the AP's environment and the specific receiver point and the expected signal strength at a location in the volume-of-interest (VoI). The model can be trained beforehand, using data collected from other environments. The space is discretized into voxels (3D volume "pixels"), where each voxel is of dimension $\delta_x \times \delta_y \times \delta_z$. The aggregate of all voxels is a tessellation of the 3D Euclidean space. The set of all voxels that are part of the VoI is denoted as $\mathcal{V}$. The location of a sender $v_s$ and receiver $v_r$ are represented as voxels, $v_s,\ v_r \in \mathcal{V}$. Each voxel is associated with a tuple value whose first component indicates the environment elements contained in it, e.g., walls, furniture, and free space, while the second component indicates the relevance of the voxel to the signal propagation from $v_s$ to $v_r$.

Under these considerations, a measurement is characterized by a VoI (i.e., the set of voxels $\mathcal{V}$), the location of the AP ($v_s$), and the location of the receiver ($v_r$). By assigning a special numeric value to $v_s$ and $v_r$, all the elements that describe a measurement can be conveniently encoded in a 4-dimensional tensor, denoted as $\mathbf{x}$. The signal strength value, in dBm, at $v_r$ is denoted as $\mathbf{y} \in \mathbb{R}$.

Our goal is to cast the prediction of the RSS at a given location as a regression problem, where we learn a function $y = f(\mathbf{x})$, such that, given a VoI and the location of the AP and the receiver, encoded as $\mathbf{x}$, provides an accurate prediction of the RSS $y$.

## IV. Dataset generation

In this section, we describe our data collection methodology. A 3D floor plan is translated into a 3D model following a manual procedure. The 3D models are then voxelized, where corresponding voxels are selected from where RSS measurements are taken. For each sampling location, a 4-dimensional tensor is constructed by assigning numerical values according to the location of the sampling point. In the end, we obtain a complete data sample, which is added to the set of all samples.

### A. 3D Floor Plan creation

A 3D model design software was used to create the 3D floor plan. The 2D floor plans were colored according to the material of the objects in it. This color encoding was consistent throughout the dataset. The 3D models were stored in a file format that could retain the different color and texture properties that were imparted to distinguish the objects from one another.

### B. Voxel Representation

We used an automated tool to voxelize a 3D model. Given the voxel dimensions, the software returns a list of $(x, y, z, r)$ values, where $(x, y, z)$ is the location of the voxel in the euclidean space, and $r$ is an integer value (i.e., the color) associated to the voxel. The software was also used to fine-tune the coloring of the voxels and to add the location of the access point.

### C. RSS samplings

The 3D floor plan was systematically divided into location points for data collection. The Location points were 30 cm apart from each other in the xy-plane and were set on three different $z$ or height values. The voxel editor tool was used to determine the coordinates of the sampling locations. At every location, the RSS value was estimated for a duration of 3 minutes.

Measurement of RSS was made at 2.442 GHz carrier-frequency using an AC1750 DB Wireless Dual-Band AC+ Gigabit Router with Tx signal power 3 dBm and bandwidth 20 MHz . Network traffic was generated from a second device in the wireless network to guarantee a continuous flow of packets from the AP. The mean of the data collected was considered as the final value for each location.

### D. Matrix creation

Once RSS estimates from all points in $V_{\mathcal{P}}$ are defined, we proceed to the generation of the dataset. For each point in $v_r \in V_{\mathcal{P}}$, we define a tensor $\mathbf{x}$ of fixed dimensions $L \times W \times H \times 2$.

Any voxel not in the VoI is assigned values $(0, 0)$. Voxels in the VoI are assigned values $(a, b)$, where $a$ is the color assigned to $v_r$ and value $b$ was assigned based on distance; 0 denoted distances over 20 meters, 10 denoted distance under 5 meters and a value 5 denoted the rest of locations.

### E. Data Augmentation

A total of 813 location points were initially collected. This amount of data seemed insufficient, and the early model training with this dataset yielded considerably larger loss values.

To augment the data, we randomly select a voxel within 1 meter distance of the original sample and then find the corresponding locations where only few RSS values were obtained and generate artificial samples. 1712 samples were obtained after performing the augmentation process.

# V. CNN Model

A CNN model was used due to its spatial filters that establish a "local connectivity pattern between neurons of adjacent layers" [4], making the architecture most suitable for spatially local input patterns such as our 3D data. The regression neural network model was made using Keras and scikit-learn libraries.

## A. Model Architecture

The model architecture contained a total of 9 layers. A Convolutional Neural Networks (CNN) layer acted as the input layer, and a Dense layer was the output layer. We used the default parameters for Adam in Tensorflow. We used a starting learning rate of $10^{-5}$ with a batch size of 64. While training, the model was fitted with a learning rate scheduler that altered every epoch's learning rate to the best rate to train the model. The data was trained and tested on a balanced data set, with appropriate data added to make the distribution equal. This was done to allow the model to predict better and generalize over a more extensive range of values. Moreover, the model weights for the best performances were saved from training.

## B. Loss Function and Model Evaluation

Mean Absolute Error (MAE) was used to track model performance. The loss measures were put in place to check and avoid over-fitting and under-fitting of the model. Model regularization strategies such as adding dropout layers and early stopping were implemented to train the model optimally for our required task. Plots of the training and validation losses were also generated to aid the model's training visually. The data was tracked on its performance on the metric of MAE, which is the difference between the actual measured data and the predicted data.

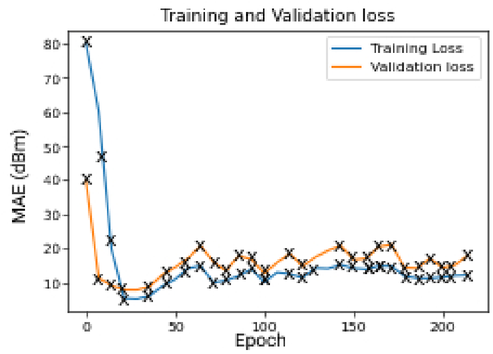
# VI. Results

The data set generated was used to train multiple models. The models differed in their architectures but were trained for an equal number of epochs and the losses were compared to ensure optimal training loss.

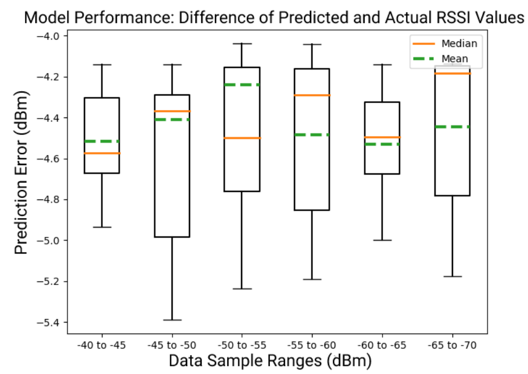
Results after 200 epochs show that 3DRSSNet displayed the best results, with its training loss staying in the range of 2-3 dBms and its validation loss in 4-5 dBms.

The training of 3DRSSNet was closely monitored, ensuring that the model does not over-fit or under-fit. Upon extensively testing, the model achieved a prediction error of 4.4 dBms, as shown in both Fig. 1a and Fig. 1b, on the test data sample, showing sufficiently accurate predictions and suitable generalizing property.

The performance of 3DRSSNet was compared with the performance of models of other known work in this field. Most existing models differ in the training data used. Data can be generated by using ray-tracing software [15] or manually




(a) Training loss and Validation loss of 3DRSSNet




(b) Model results on test data set

Fig. 1: 3DRSSNet Performance

collected at different sites (indoors or outdoors). Most models also differ on the floorplan format. Models that utilize a 3D representation of the floorplan and use data simulated from ray-tracing software and a CNN architecture such as [13] produce a model with MAE loss of 6.95-11.11 dBms. Models that use a 3D vector representation and use manually gathered data for training an Artificial Neural Network (ANN), which is a promising architecture for this problem [16], [17], produce a model with MAE loss of 15.52-16.21 dBms[1]. Models trained without utilizing the floorplans; like the ANN trained by [14] which uses no floorplan and manually measured values to produce a model with MAE loss of 5.37-5.65 dBms. Comparison of 3DRSSNet with these three models highlights our model's high performance with only MAE loss of 4.4-5.5 dBms and the need to use the 3D representation of floorplans to better aid models in predicting signal strength.

The performance of 3DRSSNet was also compared with the RSS estimations obtained from ray tracing simulations. The ray tracing simulations predicted values with a MAE loss of 11.23 dBms. This highlights the need for CNN based model to better learn factors that impact the signal strength.

The model was trained on data with and without data augmentation. This was done to understand the impact of increasing the training data's size on the loss of the model. The loss values were higher (in the range of 40 dBms) than when trained with augmented data.

| Author's Work | Floor Plan Format | Data source | Model Algorithm | MAE (dBm) |
|---|---|---|---|---|
| 3DRSSNet | 3D representation | Indoor environment | CNN | 4.4 - 5.5 |
| Krijestorac et. al. [13] | 3D representation | Ray tracing software | CNN | 6.95 - 11.11 |
| Cheng et. al. [1] | 3D vector representation | Indoor environment | ANN | 15.52-16.21 |
| Raj et. al. [14] | No Floorplan utilized | Manually measured values | ANN | 5.37-5.65 |

TABLE I: Table comparing 3DRSSNet with other model implementations

The model's performance and generalization property was tested by implementing it on a new different floorplan. Fig. 2 shows that the model performance an average loss of 5.5 dbms, denoting good generalization property.

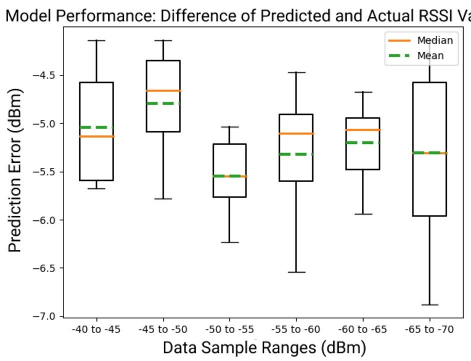



Fig. 2: Loss Value of model tested on different floor plan.

An implementation using a 2D floor plan was also tested to reinforce the need for using a 3D floor plan. The training results show generally higher MAE loss, with a training loss of around 30 dBms, and a validation loss of around 75 dBms. These results concrete the need for a more profound, rich data input and a matching model architecture to better learn from the increased data. The use of a 3D floor plan along with a deep networking model efficiently performs this task.

The implementation of the complete DL model can be found on the GitHub repository at https://github.com/YaqoobAnsari/Deep-Learning-of-Radio-Link-Quality-in-Wireless-Networks-

## VII. Conclusion

This work has presented a deep learning algorithm that can be used to predict signal propagation in a 3-D indoor environment. Our algorithm uses 3D maps of the environment to produce a stochastic prediction of received signal strength values. It outperforms existing deep learning solutions for signal strength prediction, with a substantial improvement when the locations of transmitter and receiver are known.Our algorithm has only been evaluated in a single-level indoor setting with single access points. Our future work will involve an application on multilevel structures with multiple access points and the consideration of environmental noise in the measurement.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