Radio Coverage Prediction

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by

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Contents

List of Tables

List of Figures

Abstract

In mobile communication systems, exact channel model predictions are essential for determining the cellular base station coverage region. Additionally, it enables network operators to handle coverage gap issues, select new site locations that are optimal, and improve existing network characteristics. Current prediction models rely on 3D maps, which are expensive and require frequent updates and use computationally expensive ray tracing algorithms. In this project, a multi-modal channel model prediction algorithm is proposed. The environmental features and other numerical variables are extracted from satellite images. We compared our findings with the previous work after compiling experimental observations in the 2100 MHz band and combining them with 2D maps from Cairo region to make an accurate assessment. We reach mean absolute error (MAE) 1.34 dB with 4.32 dB enhancement and for root-mean-square error (RMSE) 1.81 dB with 5.69 dB enhancement using the well-known AlexNet architecture as a baseline for our model compared to only using numerical features.

Chapter 1

Introduction

A lot of effort and time is utilized in the planning and building of the cellular wireless networks to use minimum infrastructural components to provide the best network coverage as well as delivery of quality of service.The following subsection discusses our motivation for a good coverage prediction.

1.1 Problem

In mobile communication systems,there are many problems affect on quality of received signal, besides inadequate mobile network coverage negatively impacts the Quality of Service (QoS) and capacity provided to mobile customers and devices.one of these problems is the attenuation of signal through transferring from transmitter to receiver cause with terrain, buildings characteristics (geometry, heights, construction material),angle of arrival (AoA) and so on. In addition to the problems of signal, there are problems happen depend on type of area. For example, in urban and sub-urban areas, scattering, reflections, and refractions have the most contributions to the power of received signal while in rural areas, absorption is the main contributor to it. Therefor, our problem is focused on the causes of coverage weaknesses specifically the geographical problems.

1.2 Motivation

The need for wider coverage and high-performance quality of mobile networks is critical due to the maturity of Internet penetration in today's society. One of the primary drivers of this demand is the dramatic shift toward digitization due to the Covid-19 pandemic impact. Meanwhile, the emergence of the 5G wireless standard and the increasingly complex actual operating environment of mobile networks make the traditional prediction model less reliable. With the recent advancements and promising capabilities of machine learning (ML), it is seen as an alternative to the traditional approaches for ground to ground (G2G) mobile communication coverage prediction. In order to pinpoint coverage gaps and areas where customers will have a bad customer experience, coverage power prediction is crucial in mobile communication systems. Additionally, mobile carriers select the ideal locations for new base station. By correctly predicting coverage, one may increase investment and improve customer experience.In this project, various deep learning models have been tested and evaluated to develop an deep learning-based received signal strength prediction model for mobile networks. However, the challenge is to identify a practical Deep learning model that can fulfill the computing speed criteria while still meeting the prediction accuracy.

1.3 Objective

Planning and developing a good radio network requires the use of a credible prediction model for radio signal strength. Beside the prediction of coverage, optimization of the entire system, resource allocation, and determining the best base station placement all depend on precise and effective models. Using the numerical features in parallel with satellite image,our objective is to develop Deep Channel, a multi-modal deep learning model for path loss and coverage prediction by predicting the RSRP values in 4G networks in 2100 MHz band.

Chapter 2

Background

The evolution of mobile communication systems has undergone significant changes over decades, which has created significant difficulties for the planning of mobile wireless networks. This is the fruition journey of the first-generation (1G). In the presently explored Fifth Generation (5G) network,this high-band 5G spectrum provides the anticipated increase in capacity, low latency, and quality. It is crucial for the delivery of quality service that the mobile networks are effectively covered. The prediction of coverage, the optimization of the entire system, resource allocation, and base station placement all depend on precise and effective models. In telecommunications, the coverage of a radio station is the geographic area where the station can communicate. Within this region, the server equipment (UE) will finish a call via a mobile operator network. Because of this, the UE's threshold for the received signal level necessary to finish a call accurately simulates the coverage region. The received signal level is measured in Long Term Evolution (LTE) networks through the Reference Signal Received Power (RSRP). Long Term Evolution (LTE) is defined as a wireless broadband standard for mobile communication and data transfers, built on GSM and UMTS and improving upon them in terms of bandwidth capacity and transfer speeds. It's most often connected with 4G, which was discovered in 2008. The Reference Signal Received Power (RSRP) is a measurement of the received power level in an LTE cellular network. The (RSRP) for a particular cell at a particular location is calculated by averaging the received power of various resource elements used to transmit the reference signal within the measured frequency bandwidth. Decibels to one milliwatt (dBm) are used to measure RSRP. Additionally, RSRP is employed in LTE networks as a measure of the cell coverage, which varies from the grid to the grid or area to area for a number of factors, including cell density per area, transmitted cell power, area topology, or cell type (inside cell or outdoor cell).

Since several years, many models have been developed for coverage prediction and path loss modeling. Path loss is the reduction in power density (attenuation) of an electromagnetic wave as it propagates through space. Path loss may be due to many effects, such as free-space loss, refraction, diffraction, reflection, aperture-medium coupling loss, and absorption. Path loss is also influenced by terrain contours, environment (urban or rural, vegetation and foliage), propagation medium (dry or moist air), the distance between the transmitter and the receiver, and the height and location of antennas. In recent research, RSRP and coverage prediction issues are addressed using machine learning and Deep learning approaches. The next sub-section goes over the relevant work.

2.1 Related Work

Authors in [1],compares traditional channel models to a channel model obtained using Deep Learning (DL)-techniques utilizing satellite images aided by a simple path loss model. In this paper,the authors considers path loss modelling techniques offered by state-of-the-art stochastic models and a ray-tracing model for comparison and evaluation. The authors showed that, Accurate path loss prediction with improved generalization using satellite images can be achieved with the use of convoluted neural networks. A gain of 1 dB has been achieved at 811 MHz, and 4.7 dB at 2630 MHz, compared to traditional modelling techniques such as ray tracing and empirical models.

The authors in [2], provided an algorithm to estimate the channel parameters (precisely, the pass loss exponent and the shadowing standard deviation) using a CNN architecture by utilizing satellite images.

The authors in this paper [3], presents prediction path loss models in an urban environment for cellular networks with the help of machine learning methods. For this goal, Support Vector Regression (SVR), Random Forest (RF) and K-Nearest Neighbor (KNN) algorithms are exploited and assessed. The results reveal that all the evaluated algorithms forecast path loss with a remarkable accuracy, providing root-mean-square errors on the order of 2.1 - 2.2 dB for

LOS and 3.4 - 4.1 dB for NLOS locations, respectively.

The authors in this paper [4] used a U-NET CNN architecture to predict signal strength in different locations using 3D maps of the subject area.

The authors in this paper [5], present a novel model-aided deep learning approach for path loss prediction, which implicitly extracts radio propagation characteristics from top-view geographical images of the receiver location. They applied the proposed method on an extensive real-world data set consisting of five different scenarios and more than 125.000 individual measurements and it is found that 1) the novel approach reduces the average prediction error by up to 53 % in comparison to ray-tracing techniques, 2) A distance of 250 - 300 meters spanned by the images offer the necessary level of detail, 3) Predictions with a root-mean-squared error of 6 dB is achieved across inherently different data sources.

The authors in this paper [6], presents an algorithm that relies on samples of signal strength collected across the prediction space and a 3D map of the environment, which enables it to predict the scattering of radio waves through the environment using U-NET CNN architecture. This approach differs from most existing approaches in that it does not require the knowledge of the transmitter location, it does not require side channel information such as attenuation and shadowing parameters.

In this paper [6] , the authors developed a machine learning-based modelling mechanism for the UAV air-to-air (AA) path loss.they used the ray-tracing software to generate the data for an urban AA scenario,The models have been learned by two machine learning algorithms, Random Forest and KNN.

In [7], used carefully designed input features and neural-network architecture to capture topographical information with FadeNet that is a convolutional neural-network enabled alternative for predicting large-scale fading with high computation speed and accuracy.

FadeNet can achieve a prediction accuracy of 5.6 decibels in RMSE. In addition, by leveraging the parallel processing capabilities of a graphics processing unit, FadeNet can reduce the prediction time by 40X 1000X in comparison to industry prevalent methods like ray-tracing.

The authors in [8], presented a deep learning model to predict the path loss for a wireless communication network by extracting some defined features from satellite images basedon specific types of objects and using Principal Component Analysis (PCA) to generate the low-dimensional environmental features to be used by the deep learning model.

The authors in [9], presented a deep learning model to predict the large-scale channel fading in mmWave by designing input features and neural-network architecture to capture topographical information around the base station coverage area using U-Net CNN architecture.

The authors in [10] used the Machine learning methods, such as Artificial Neural Networks and Random Forests to predicte the propagation path loss ,these models was carried out for the two NB-IoT bands at 900 MHz and 1800MHz. also have been trained and tested for three different input data categories, performing remarkably alike for all cases.they found that all input types and for each machine learning method, predictions are more accurate for the 900 MHz case rather than for the 1800 MHz.

However, the majority of earlier efforts still have several limitations and concerns with respect to their applicability and acknowledged accuracy from the perspective of service providers

- Ray tracing, which is erroneous and impractical, is used as a reference in the majority of the current work. An accurate comparison of the accepted coverage prediction accuracy, particularly for investment allocation, cannot be made by relying solely on ray tracing.

- Without supporting handcrafted features, models that employ satellite maps cannot capture all environmental features.The majority of the current work makes use of a satellite map with a high level of zoom, which cannot adequately capture the topographical features of the region.

- Lastly, to the best of our knowledge, no previous work with substantial drive test data in a broad area with several base stations can be utilised as the reference in the comparison to find practical results that would effectively influence service provider's plans.

Chapter 3

Methodology

3.1 Dataset

This section introduces the dataset used in the project. It is a combination of both numerical features (drive test field measurements) with some extracted engineered features and the online satellite images corresponding to a specific locations.

3.1.1 Drive Test Data

Drive tests is one of the main sources to collect measurements data from the field. Such measurements are usually carried out to be used as a primary indication of the coverage and performance Key Performance Indicators (KPIs). The main reasons for drive tests are: (1) Coverage optimization based on field measurements enhances the coverage map built from deterministic or stochastic models discussed in Section I; (2) It enables mobility optimization to detect handover failures; (3) Capacity optimization, using drive tests measurements, allows the operators to detect low throughput areas and through correlation with the coverage map it enables detecting the coverage holes and gaps that impact the capacity. Drive tests are usually carried out on a regular basis to detect any coverage or network issues and in many cases after any optimization action taken by the service provider engineering team such as frequency shuffling or re-farming. Drive test is a cost and human efforts process; techniques are required to minimize drive test measurements to save service providers OPEX cost [11]. Data is collected through intensive drive tests in a suburban area using the TEMS solution [12], an autonomous solution that uses smartphones to test data and voice services. Data logs are uploaded or saved periodically for further post-analysis. The used testing unit is a commercial smartphone to simulate a real customer's experience. In our model, the log files were collected through Samsung Galaxy Note8. The car's speed was an average road speed of 40 KM /h, sampling interval of 24 msec, and the mobile was locked in 4G network using the 2100 MHz B1 band, with carrier bandwidth of 15 MHz. Different messages exchanged between the UE and the base station.The readings Were selected for downlink messages. A builtin GPS module was used for accurate coordinates synchronization.

3.1.2 Satellite Maps API

Satellite maps have been significantly improved and are now available at a low cost from different providers. The improvement includes various maps with varying zoom levels to capture different types of objects and even street-level details. Also, map providers now support on-the-shelf APIs to facilitate integration with other systems with different categories. In our proposed work, we use Google Cloud Platform, a suite of cloud computing services offered by Google. On the satellite maps (API), we combine the collected data with the online satellite map provider to download the satellite image corresponding to a specific location. We utilize the static maps API to download satellite images in all geographical locations where we collected the drive test data. The center of the image corresponds to each point in the drive test data. We use zoom level 19 and an image size of 640×640, which gives 0.298 m/pixel resolution to capture all environmental details.

3.1.3 Cell Configuration

In the third module, cell-specific parameters and configuration (operating frequency, transmitted power, antenna heights, etc.) and the geographical locations of the existing base stations. This data is in the planning tool that the service providers' engineers use to plan and optimize the network. Planning includes the optimal allocation of the new base station to achieve specific coverage and customer experience requirements. At the same time, optimizations aim to find the optimum parameters to operate the network efficiently for the same coverage and customer experience requirements. This data is collected with post-processing to fit into the multi-modal model and accurately calculate the hand-crafted features.

The size of the dataset is 86904 samples, Collected - by using drive test techniques - from different locations in Cairo city.

3.1.4 Statistics Analysis

```
[41] test_drive_df.describe()
```

	Rec_Lat	Rec_Long	RSRP	serving_Lat	serving_Long	distance	Bearing_angle	PL
count	86311.000000	86311.000000	86311.000000	86311.000000	86311.000000	86311.000000	86311.000000	86311.000000
mean	30.010822	31.456926	-82.199889	30.010614	31.456979	0.316151	-2.871994	113.145304
std	0.007326	0.006574	9.340947	0.007621	0.006772	0.171972	106.055691	9.277511
min	29.999150	31.445830	-113.875000	29.998269	31.437775	0.002481	-179.985074	43.153312
25%	30.004210	31.451570	-88.750000	30.003575	31.452244	0.192794	-101.708200	108.195168
50%	30.009940	31.456670	-81.437500	30.010572	31.456667	0.292458	1.019477	114.421660
75%	30.016770	31.461430	-75.312500	30.016964	31.461689	0.400959	88.522668	119.136626
max	30.025250	31.474660	-54.875000	30.029353	31.481494	1.617984	180.000000	139.982637

Figure 3.1: Statistics Analysis

3.2 Data Preprocessing

After collecting the data, we did some preprocessing on our data to improve the overall data quality. Data cleaning is particularly done as part of data preprocessing to clean the data by filling in missing values, smoothing the noisy data, resolving inconsistencies, and removing outliers. The following subsection discusses the preprocessing steps.

3.2.1 Missing Values

As we see, there are 593 missing values in the RSRP column.

```
[17] test_drive_df.isnull().sum()

Rec_Lat            0
Rec_Long           0
RSRP             593
serving_Lat        0
serving_Long       0
distance           0
Bearing_angle      0
dtype: int64
```

Figure 3.2: A Values Is Missing

We handled that by filling them with previous value for RSRP because the locations of the receivers and each other are close so we can consider the RSRP value of the previous location from it.

```
[40] test_drive_df.isnull().sum()

     Rec_Lat          0
     Rec_Long         0
     RSRP             0
     serving_Lat      0
     serving_Long     0
     distance         0
     Bearing_angle    0
     PL               0
```

Figure 3.3: A Values Is Missing

3.2.2 Duplicated Data

We checked the duplicated data and there are no duplicated records in our data.

```
[30] #check duplication
     test_drive_df.duplicated().sum()

     0
```

Figure 3.4: Duplicated Data

3.2.3 Outliers

Outliers and inconsistent data points often tend to disturb the model's overall learning, leading to false predictions, so we checked the outliers in the data using boxplot and we concluded that there were no outliers.

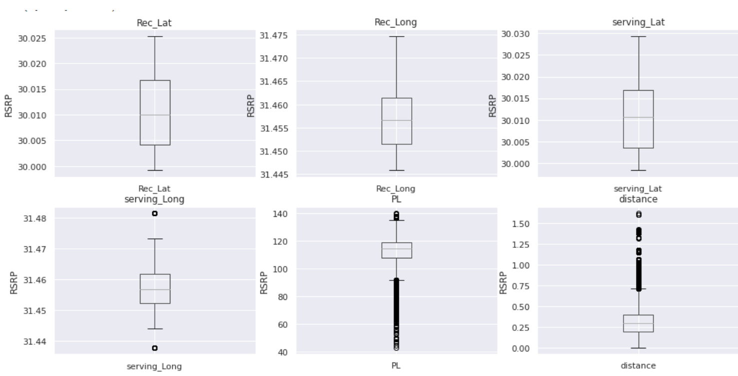

Figure 3.5: Outlier

3.2.4 Resizing Images

It is considered an essential step of image processing for many reasons. Resizing the images reduces the computational power required to run the models or do any operations on them. We resized our whole images to become (160,160) instead of (640,640) to suit the model.

3.2.5 Data Augmentation

In general, data augmentation in data analysis is a procedure utilized to expand the measure of data by adding somewhat revised copies of previously existing data or recently synthesized data from existing data. We augmented the numerical data to become double by adding some changes to the longitude and latitude of the receivers, so the sample size became 173808 instead of 86904 records, and for satellite images, we used the same images for the new records.

3.2.6 Feature Engineering

Feature engineering can be categorized into two main types. The first is handcrafted features that use domain knowledge experience to define and extract the needed features. The second is the self-learned features that can be learned and extracted automatically using a machine learning algorithm. In our model, we use a mix between the two types as follows:

1. Handcrafted Features

   - The distance between the transmitter and receiver, is a critical feature in path loss model calculations.
   - Geographical coordinates (Latitude and longitude) for the receiver are used as landmark features for the location LAT, LONG.
   - Adding a simple path loss model as a feature to aid and guide the model in the right and accurate direction of convergence, we use the Hata-Okumara model.

     $PLurban = 69.55 + 26\log(fc) - 13.82\log(hte) - a(hre) + (44.9 - 6.55\log(ht)) \times \log(d) + Cm$ more-info
   - Bearing angle between the transmitter and receiver Assume that we need to get the bearing between two points (Lat1, Long1) and (Lat2, Long2), we use equations as follow:

     $deltalong = (Long2 - Long1)$

     $y = sin(deltalong) * cos(Lat2)$

     $x = cos(Lat1) * sin(Lat2) - sin(Lat1) * cos(Lat2) * cos(deltalong)$

     $bearing = tan^{-1}(x, y)$ more-info

The new columns added to dataset :

	Rec_Lat	Rec_Long	RSRP	serving_Lat	serving_Long	distance	Bearing_angle	PL
0	30.01471	31.45804	-66.5625	30.010772	31.456667	0.456179	-163.196082	121.064588
1	30.01472	31.45804	-66.5625	30.010772	31.456667	0.457239	-163.236257	121.099297
2	30.01472	31.45805	-66.5625	30.010772	31.456667	0.457520	-163.121105	121.108460
3	30.01472	31.45806	-66.8125	30.010772	31.456667	0.457802	-163.006094	121.117678
4	30.01472	31.45807	-67.3125	30.010772	31.456667	0.458086	-162.891224	121.126951

Figure 3.6: Final dataset

2. Self-learned Features:

   It is obvious that the area characteristic that has the greatest impact on the RSRP value is the main contributor to the path loss model. As a result, a key component of the path loss model is capturing the geo-statistical information.

   In our suggested model, we extract the geo-statistical information about the environment from satellite images. When using a satellite map, we can take into account a variety of features, including the direct line of sight (LoS) path between TX and RX, detect the type of objects in the direct path, their contributions to the direct path, and the environment and obstructions in the area of the receiver. That is why we use a well-known convolutional neural network architecture to extract the essential features that impact the output (RSRP).

In this table we showed some columns definitions

Column name	Description
Rec-Lat	receiver latitude
Rec-Long	receiver longitude
serving-Lat	transmitter latitude
serving-Long	transmitter longitude
Distance	distance between the transmitter and receive
RSRP	defines the average power received for the Reference Signal (RS) transmitted from a cell in LTE networks, this is our the label.

Table 3.1: Columns Description

3.3 Data Visualization

Data visualization is one of the core skills in data science. In order to start building useful models, we need to explore the variables in great depth before we can move on to building a model or doing something else with the data.

3.3.1 Correlation Matrix

Correlation is a statistical technique that shows how two variables are related. It is used to find the pairwise correlation of all columns in the dataframe.

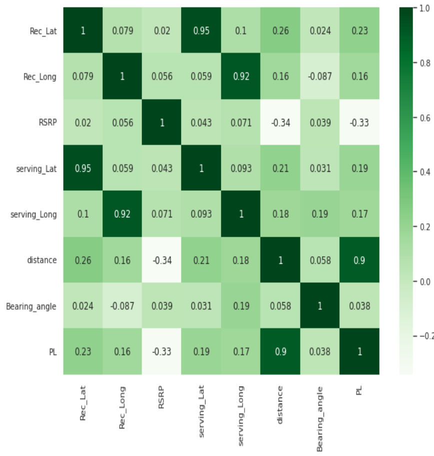

Figure 3.7: Correlation Matrix

3.3.2 Check Distribution

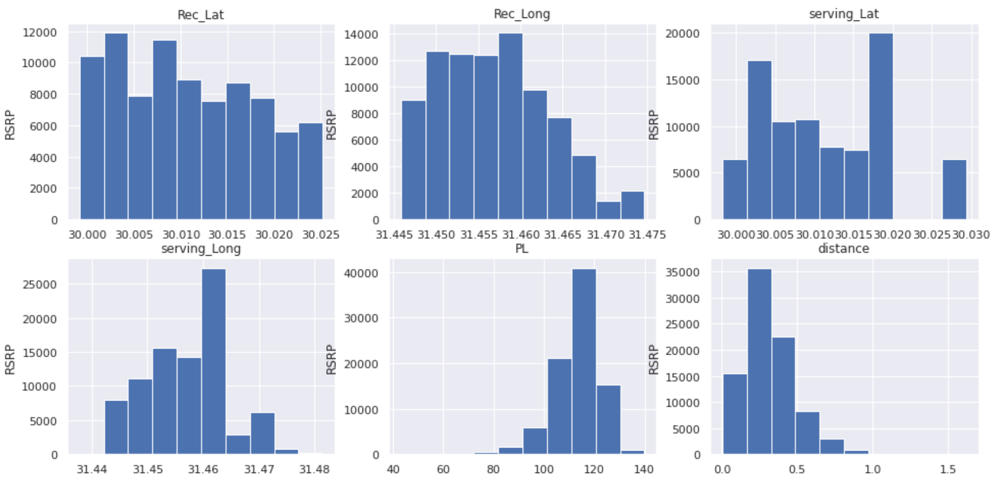

Figure 3.8: Distribution Of Data

3.3.3 pairplot

This pairplot gives us a reasonable idea about variables relationships.

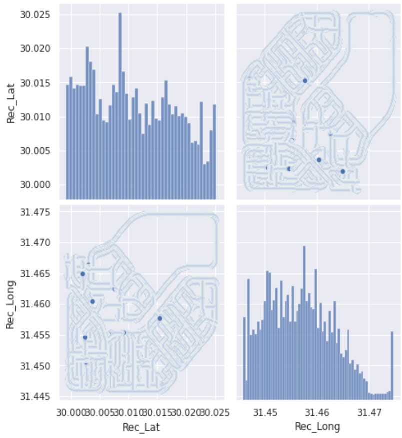

Figure 3.9: pairPlot For Longitude and Latitude

3.4 Model Architecture

In this section, we will present the models' structures. We have two approaches to training our models. The following subsection presents them in detail.

3.4.1 The First Approach

This network (in figure 3.10) is a neural network(NN) only to extract features from the numerical modality by adjusting neural network weights that influence the RSRP values.

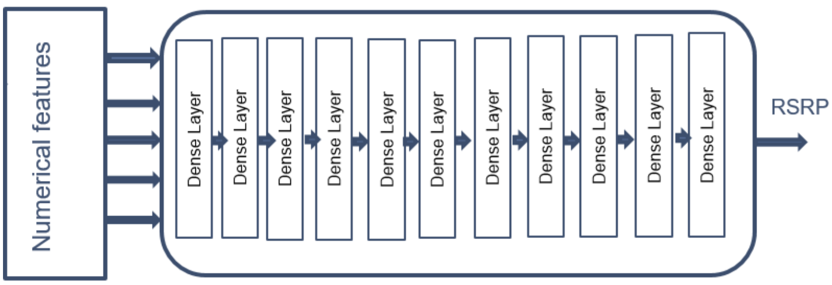

Figure 3.10: Neural network model architecture for feature extraction from the numerical modality.

Network	Type	Number of Neurons	Activation
NN Network	Dense Layer	64	relu
	Dense Layer	64	relu
	Dense Layer	64	relu
	Dense Layer	64	relu
	Dense Layer	128	relu
	Dense Layer	128	relu
	Dense Layer	64	relu
	Dense Layer	64	relu
	Dense Layer	64	relu
	Dense Layer	64	relu
	Dense Layer	1	relu

Table 3.2: Details on the architecture of Neural network model.

3.4.2 The Second Approach

This subsection presents the network structure for the second approach. Figure 3.11 shows the block diagram and components of the multi-modal model. We have three main networks. The first is one of the well-known backbone networks for computer vision, AlexNet. We are using the well-known ConvNet AlexNet architecture, which was proposed by Alex Krizhevsky et al.[13]. AlexNet, one of the dominant backbone networks used in image feature extraction, won the ImageNet LSVRC-2010 competition to classify 1.2 million high-resolution images into 1000 different classes. It consists of five main convolutional blocks. Each block has building layers with different convolution kernel filters, Relu activation functions, and a batch normalization layer followed by flatten and dense layers. Figure 3.12 shows the detailed configuration and parameters for the AlexNet network. We use AlexNet for image modality to extract the features that impact the RSRP value. The second network (Network 1 in Figure 3.11) is a feed-forward neural network (FNN) to extract features from the numerical modality by adjusting neural network weights that influence the RSRP values. We concatenate the extracted features from networks one and two. We use a final FNN (Network 2 figure 3.11) to mix and produce a regression prediction for the RSRP value for the output of the two networks (Network 1 and AlexNet). Table 3.2 shows the detailed architecture of networks 1 and 2.

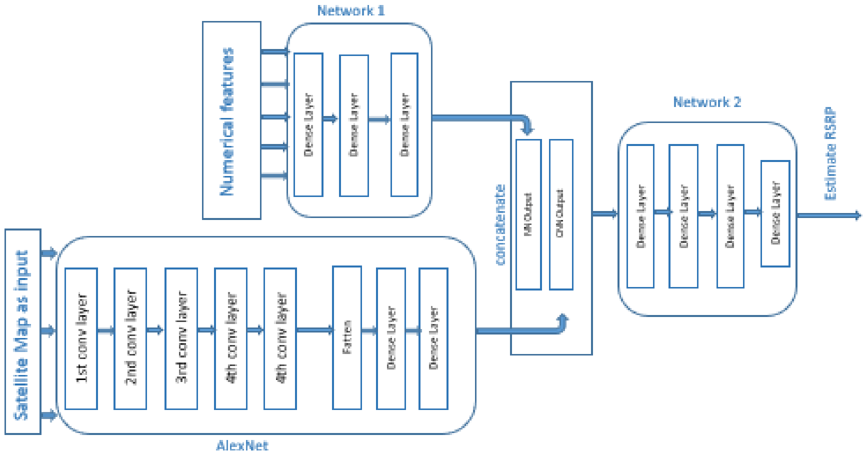

Figure 3.11: Multi-modal model architecture. Network 1 for feature extraction from the first modality, AlexNet for the environmental features extraction from the satellite images (the second modality) and Network 2 for the concatenate between the two modalities.

Network	Type	Number of Neurons	Activation
Network 1	Dense Layer	64	relu
	Dense Layer	64	relu
	Dense Layer	64	relu
Network 2	Dense Layer	128	relu
	Dense Layer	64	relu
	Dense Layer	32	relu
	Dense Layer	1	linear

Table 3.3: Details on the architecture of Networks 1 and 2.

Layer	Type	Input	Filter Size	Number of filters	Output
1st Conv Block	Conv2d	160x160x3	(11x11)	96	40x40x96
	Activation	Relu Activation			
	Batch Normalization	Batch Normalization Layer			
	Max Pooling	40x40x96	(2x2)		20x20x96
2nd Conv Block	Conv2d	20x20x96	(5x5)	256	20x20x256
	Activation	Relu Activation			
	Batch Normalization	Batch Normalization Layer			
	Max Pooling	20x20x256	(2x2)		10x10x256
3rd Conv Block	Conv2d	10x10x256	(3x3)	384	10x10x384
	Activation	Relu Activation			
	Batch Normalization	Batch Normalization Layer			
4th Conv Block	Conv2d	10x10x384	(3x3)	384	10x10x384
	Activation	Relu Activation			
	Batch Normalization	Batch Normalization Layer			
5th Conv Block	Conv2d	10x10x384	(3x3)	256	10x10x256
	Activation	Relu Activation			
	Batch Normalization	Batch Normalization Layer			
	Max Pooling	10x10x256	(2x2)		5x5x256
6th Layer	Flatten	Flatten Layer Output 6400			
7th Layer	Dense	Dense Layer with 1024 Neuron			
8th Layer	Dense	Dense Layer with 256 Neuron			

Figure 3.12: ALexNet network architecture details.

3.5 Performance Evaluation

In this section, we present the results of our models using two main metrics in regression problems to evaluate the obtained results, which are the Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE). They are defined by the following two equations.

$$\text{MAE} = \frac{\sum_{i=1}^{n} |yi - xi|^2}{n}$$

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (yi - xi)^2}{n}}$$

Chapter 4

Results

4.1 Numerical Features Model

As for this approach, it used numerical features only as an input for the feed forward neural network model (explained in section 3.3.1). The results for MAE for the Cairo dataset shown in Figure 4.1 is 5.66 dB, and for RMSE is 7.5 dB. These are relatively high values that we can not depend on in actual practical predictions. That is because the RSRP values in the Cairo region suffer from different conditions (scattering, reflection, refraction) that significantly affect the RSRP. So, the model couldn't catch the many features that affect the RSRP value prediction.

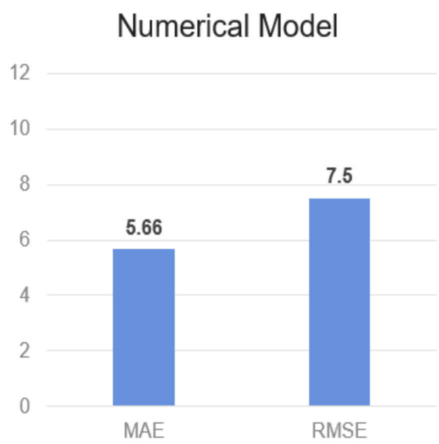

Figure 4.1: Numerical Results.

4.2 Deep Channel Multi-modal Model

As for this approach, it used both datasets, the numerical features (test drive data) along with satellite images as inputs for the multi-modal model (explained in section 3.3.2). The results for MAE for the Cairo dataset shown in Figure 4.2 is 1.34 dB with 4.32 dB enhancement, and for RMSE is 1.81 dB with 5.69 dB enhancement.

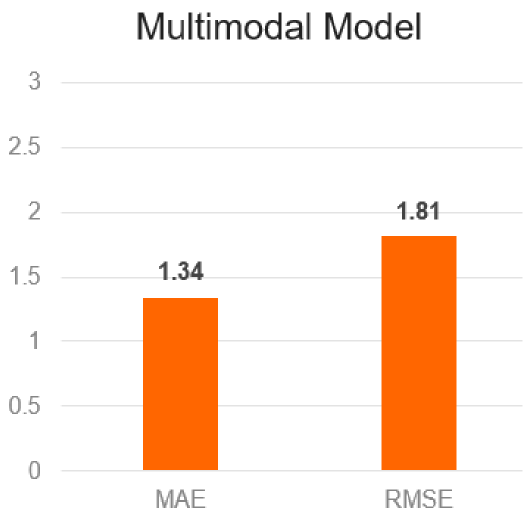

Figure 4.2: Multi-modal Results.

4.3 Comparison between two approaches

It is clear in Figure 4.3 that, after we used satellite images, the model was able to capture more features that affected the RSRP values prediction, and that enhanced the model performance and reduced the error values.

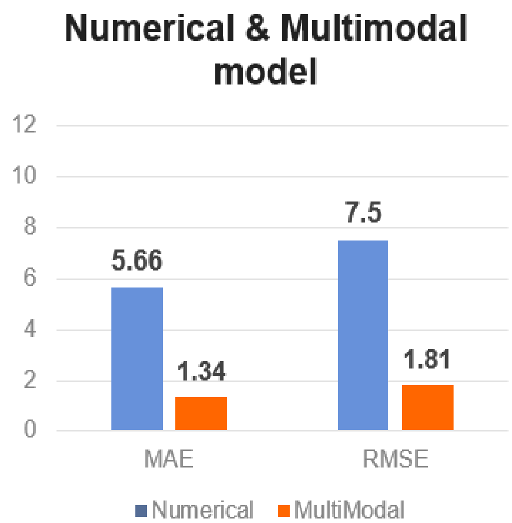

Figure 4.3: Multi-modal And Numerical Features Results.

Chapter 5

Discussion

In our result section, we show the robustness of the DeepChannel model and its high accuracy. During the planning phase, service providers' planning engineers choose the best location for the new base station to solve coverage problems. And as stated in section 4.2, ray tracing models are inaccurate, so service providers cannot rely on this data as the main input to the planning phase. The second method is to create the coverage map using drive test data from each newly deployed base station, which is a costly and time-consuming process. As a result, a trained model based on various area characteristics is used to estimate the coverage map with high accuracy. As a result, the DeepChannel model is used to create the coverage map while taking into account the environmental characteristics of the area and creating an accurate channel model that can be used in the planning process of selecting the best base station locations. The next service provider process is to optimise the current network base station to address customer coverage or capacity complaints resulting from a bad experience. To solve the problem, the optimization process involves changing some configuration parameters. To examine the result of an action taken in the optimization process, we should rely on ray tracing techniques, which are not accurate as explained in section 4.2, or drive test data. Because the optimization process is based on trial and error, a large amount of drive test data is required after any action to examine the results. As a result, the DeepChannel model is used to examine the optimization process's output. However, the DeepChannel model's application is limited to the parameters associated with coverage parameters. To examine the result of an action taken in the optimization process, we should rely on ray tracing techniques, which are not accurate as explained in section 4.2, or drive test data. Because the optimization process is based on trial and error, a large amount of drive test data is required after any action to examine the results. As a result, the DeepChannel model is used to examine the optimization process's output. However, the DeepChannel model's application is limited to the parameters associated with coverage parameters.

5.1 Limitations and challenges

There were some limitations and challenges that we faced during the project, and they are divided into several reasons as follows, which is understanding the problem, this was a great challenge for us because we do not have a background in communications engineering, but we overcame this challenge with a lot of research in similar research papers and with the help of experts in the field; as well as the total data volume that exceeded 23 gigabytes after we compressed it, which took four days to download this volume from Google Map, and it needed high computing capabilities like more CPU and GPU, especially since the data was images and needed a lot of computational operations on it and a lot of time needed to preprocess it.

5.2 Summary

As a summary, Instead of experts going by themselves to put the transmitters in certain places and then measure the strength of the received signal in the receiving places, this process takes a lot of money, time and effort because it depends on experience. We can consider the proposed Deep Channel multi-modal model in this and it will produce the desired results. It saves for them all the previous problems of time, effort and money spent.

5.3 Conclusion

Coverage prediction is critical in the day-to-day operations of mobile service providers in order to improve customer experiences and make smart investments. Thus, we introduced DeepChannel, a multi-modal deep learning model for path loss and coverage prediction in 4G networks in 2100 MHz band. When compared to state-of-the-art models, our proposed architecture with handcrafted features achieves a high prediction accuracy. The use of satellite maps as a new modality with numerical features has greatly improved prediction accuracy. We validated our model using physical drive test data from the Cairo region. We compared our findings to drive test data, which is a more accurate comparison than ray tracing data. The results demonstrated that the DeepChannel model was highly accurate, with a distribution that was similar to the drive test data. DeepChannel employs multiple modalities to extract environmental features that influence path loss in 4G networks with varying area characteristics.

5.4 Future Work

We will use image semantic segmentation to capture the different objects from the satellite image. That can enhance the model performance and reduce the error, as it will provide the most features that affect RSRP value prediction. Also, we can test DeepChannel in different operating frequency bands and for new evolving mobile technologies such as 5G, 6G. As for checking more enhancements to our data, we can test more different approaches. We can also optimise the hyperparameter techniques to check the improvement of the model's performance.

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References

[1] Akob Thrane, Darko Zibar, and Henrik Lehrmann Christiansen. Model-aided deep learning method for path loss prediction in mobile communication systems at 2.6 ghz. https://ieeexplore.ieee.org/document/8950164, January 2020.

[2] T. Baykas O. Ahmadien, H. F. Ates and B. K. Gunturk. Predicting path loss distribution of an area from satellite images using deep learning. https://ieeexplore.ieee.org/document/9057515, 2020.

[3] Nektarios Moraitis, Lefteris Tsipi, and Demosthenes Vouyioukas. Machine learning-based methods for path loss prediction in urban environment for lte networks. https://ieeexplore.ieee.org/document/9253369, 2020.

[4] Enes Krijestorac; Samer Hanna; Danijela Cabric. Spatial signal strength prediction using 3d maps and deep learning. https://ieeexplore.ieee.org/document/9500970, 14-23 June 2021.

[5] Jakob Thrane; Benjamin Sliwa; Christian Wietfeld; Henrik L. Christiansen. Deep learning-based signal strength prediction using geographical images and expert knowledge. https://ieeexplore.ieee.org/document/9322089, 2020.

[6] 1 Guanshu Yang 1 Zunwen He 1 Yan Zhang, 1 Jinxiao Wen and Xinran Luo1. Air-to-air path loss prediction based on machine learning methods in urban environments. https://doi.org/10.1155/2018/8489326, 13 Jun 2018.

[7] BINGWEN ZHANG1 VISHNU V. RATNAM and SOONYOUNG LEE2. Fadenet: Deep learning-based mm-wave large-scale channel fading predictionand its applications. https://ieeexplore.ieee.org/document/9311729, 31Dec 2020. DOI: 10.1109/ACCESS.2020.3048583.

[8] LINA WU, DANPING HE, KE GUAN 1 2 (Senior Member IEEE) BO AI, JIAN WANG1 HANG QI4, and (Senior Member IEEE) ZHANGDUI ZHONG 1, 2. Artificial neural network based path loss prediction for wireless communication network. https://ieeexplore.ieee.org/document/9246512, 02 November 2020. DOI: 10.1109/ACCESS.2020.3035209.

[9] SOTIRIOS P. SOTIROUDIS1 , PANAGIOTIS SARIGIANNIDIS , SOTIRIOS K. GOUDOS , AND KATHERINE SIAKAVARA1. Fusing diverse input modalities for path loss prediction: A deep learning approach. https://ieeexplore.ieee.org/document/9354618, February 15, 2021. DOI: 10.1109/ACCESS.2021.3059589.

[10] Sotirios P. Sotiroudis; Sotirios K. Goudos; Katherine Siakavara . Neural networks and random forests: A comparison regarding prediction of propagation path loss for nb-iot networks. https://ieeexplore.ieee.org/document/8741751, 20 June 2019. DOI: 10.1109/MOCAST.2019.8741751.

[11] D. baumann, "minimization of drive tests (mdt) in mobile communication networks," in proc. zum seminar future internet (fi) innov. internet technologien mobilkommunikation (iitm), vol. 9, 2014, pp. 1–7. http://www-cs-faculty.stanford.edu/~uno/abcde.html.

[12] Tems portfolio. mobile network optimization. accessed: Sep. 6, 2021. https://www.infovista.com/tems.

[13] I. Sutskever A. Krizhevsky and G. E. Hinton. "imagenet classification with deep convolutional neural networks," in proc. adv. neural inf. process. syst., vol. 25, 2012, pp. 1–9.