Field strength prediction based on deep learning under small sample data

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The accurate prediction of radio wave propagation is extremely important for wireless network planning and optimization. However, inexact matching between the traditional empirical model and actual propagation environments, as well as the insufficiency of the sample data required for training a deep learning model, lead to unsatisfactory prediction results. Our paper proposes a field strength prediction model based on a deep neural network that is aimed at a tiny dataset composed of the geographic information and corresponding satellite images of a target area. This model connects two pretrained networks to minimize the parameters to be learned. Simultaneously, we construct a convolutional neural network (CNN) model for comparison based on a previous advanced study in this field. Experimental results show that the proposed model can obtain the same accuracy as that of previously developed CNN models while requiring less data.

Introduction: Radio wave propagation prediction possesses significant implications for wireless network planning and optimization [1]. The propagation process of radio waves is extremely complex and is influenced by numerous external factors, such as terrain, weather and environmental characteristics [2]. Many studies have been conducted on radio wave prediction and channel modeling, such as those on traditional deterministic models [3], stochastic models [4], and some models based on ray tracing methods [5]. However, deterministic models are computationally expensive, while most stochastic models ignore the influences of environmental factors [6], resulting in limited prediction accuracy. Ray tracing methods have the same problem as that faced by deterministic models; that is, they require detailed geographic data and enormous computational complexity [7].

In recent years, many scholars have considered employing machine learning to obtain the large-scale propagation characteristics of various communication environments, such as urban [8, 9], rural [10, 11] and mixed environments [12], as well as some special environments (tunnels, mines, roads, etc.) [13–15]. For such methods, an increase in the number of input feature types helps to achieve improved prediction accuracy since this enables more comprehensive descriptions of environmental characteristics.

Therefore, recent studies have taken satellite images as an additional input feature type because satellite images can intuitively represent the environmental characteristics of research areas. Jakob et al. proposed a model by combining a fully connected network (FCN) and a convolutional neural network (CNN) [16]; additionally, they adopted latitudes, longitudes, the distance between the transmitter and receiver and satellite images as model inputs. With the application of satellite images, the prediction accuracy was significantly improved. Furthermore, this academic team introduced a model-aided deep learning method to enhance the prediction of path losses in some invisible locations [17]. The realizations of these works were based on the presence of ideal datasets. The authors collected relatively complete data through drive test measurements, but it is difficult for many researchers to obtain complete data.

The contributions of this paper are summarized as follows. We propose a model based on a deep neural network to accurately predict field strength in cases with less sample data. The model adopts the transfer learning method and is composed of two pretrained submodels; therefore, the number of parameters it needs to learn is greatly reduced so that it can accurately predict field strength under small sample size. Simultaneously, we refer to the previous study in [16] to construct a CNN model with sufficient sample data for comparison purposes. The results show that the prediction accuracy of the proposed model is not inferior to that of the previously developed CNN model and our proposed model requires only a small number of samples.

Data generation: The training, validation, and testing of all models covered in this paper are based on one dataset. The input of the model is further defined as:

$$x_n = [lat, lon, H, I].$$

where lat and lon represent the longitude and latitude coordinates of the measurement point, respectively, H denotes the elevation of the measurement point, and I denotes the satellite image of a certain area centered on the measurement point. Through drive test measurements, we acquire measured radio wave propagation data in a suburb of Nanjing. The data include the longitude and latitude of each measurement point and the corresponding field strength, with a frequency of 2590 MHz. The measurement area is a 3 km × 2 km rectangular area, including a certain number of buildings, roads, vegetation, lakes, hills, farmland and other various environmental features. Finally, 11,298 usable samples are obtained after data preprocessing.

To obtain the elevation data of each measurement point, we adopt the digital elevation model (DEM) of Nanjing and then use Python's GDAL library to read the DEM data and query the elevation information based on the latitude and longitude values. Considering the large number of images required in this paper, we download an internet tile map and obtain satellite images with the desired size after a series of processing steps conducted from the perspective of convenience and economy. Specifically, we use the longitude and latitude values of the measurement points to obtain an internet tile map and then achieve an ideal image size through stitching and cutting, which can be completed with Python. The area covered by the satellite images with sizes of 224 × 224 pixels is approximately ∼ 168 × 168 m, the number of satellite images is the same as the number of measurement points, and these images have three color channels (RGB). The satellite images of two adjacent points possess a high degree of overlap, which is beneficial for model prediction. The whole process of data generation is shown in Fig. 1.

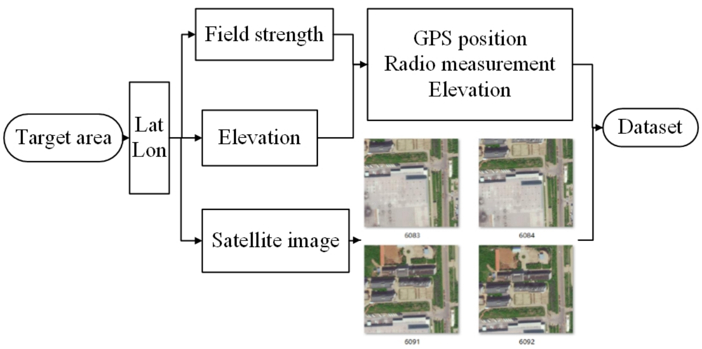


Fig 1 *Flow chart of the data generation process.*

Deep neural network construction under small samples: In this section, we construct a prediction model that is based on a deep neural network and is suitable for small samples. Four input types (latitudes, longitudes, elevations and satellite images) and one output type (field strength) are utilized by this model, whose structure is shown in Fig. 2. We use a partial dataset (1573 samples) for model training, validation, and testing.

To ensure that the prediction effect obtained with small sample data is strong, it is necessary to reduce the number of parameters to be learned. Therefore, we incorporate the idea of transfer learning, start with the pretrained model, and fine-tune the model based on the small given dataset to ensure the accuracy of model prediction. PyTorch provides numerous off-the-shelf pretrained models, and we use the trained ResNet18 [18] model to process satellite images. The module used to process the latitude, longitude and elevation data is a three-layer FCN (named NN1), which was trained in another study of ours [19]. In this study, we obtain the DEM of a certain area from the Internet. WinProp [20] is an excellent software program for radio propagation modeling and radio network planning. It can calculate radio data such as the field strengths and path losses at different locations in a region by setting appropriate calculation parameters and inputting the DEM. We use the field strength data generated by a WinProp simulation and the elevation data corresponding to these positions for training the model, and finally, the model can accu-

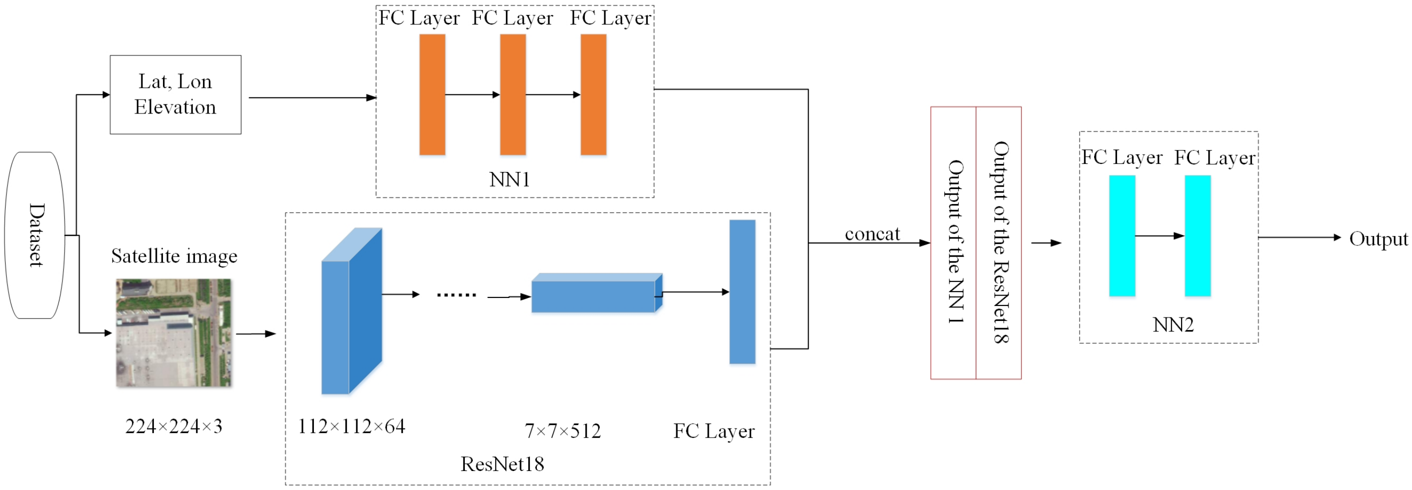


Fig 2 *The newly proposed model uses two pretraining submodels (ResNet18 and NN1) to process satellite images and longitude, latitude and elevation data. The output tensors of NN1 and ResNet18 are concatenated as the input of NN2.*

Table 1. Some important structural parameters of the proposed model.

Output size of NN1	128 × 2
Output size of ResNet18	512 × 50
NN2 layer size	[16, 1]

Note: The output size of the last layer of NN1 is changed from 128 × 1 to 128 × 2, and the output size of the last layer of ResNet18 is changed from 512 × 1000 to 512 × 50.

Table 2. The relevant parameters of the previous model.

Channels	[100, 50, 20, 3]
Kernel size	[(5,5), (3,3), (3,3), (2,2)]
Max pooling	[2, 2, 2, 2]
NN1 layer size	[64, 64, 3]
NN2 layer size	[16, 1]

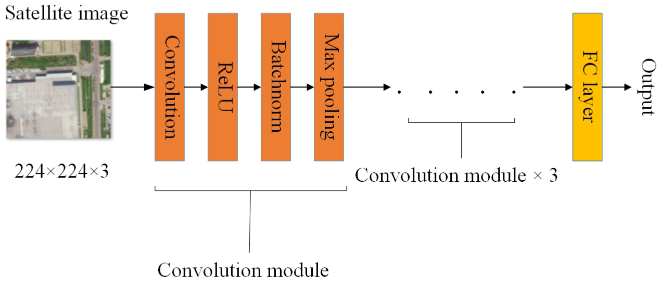


Fig 3 *The partial structure of the previous model.*

rately predict a field strength value through the input latitude, longitude and elevation data.

Furthermore, we modify the structures of the last fully connected layers of ResNet18 and NN1 to minimize the number of model parameters to be learned. Then, the output tensors of NN1 and ResNet18 are concatenated as the input of NN2, which is a new two-layer FCN without pretraining. The hyperparameter optimization process of the model is carried out by Optuna, and the output sizes of the last layers of ResNet18 and NN1 are determined. Some important structural parameters of the proposed model are shown in Table 1.

Construction of a comparison model with sufficient sample data using a previous study : To verify the superiority of our proposed network (named the proposed model), we compare it with the prediction model (named the previous model) referred to in [16]. The previous model is trained, validated and tested with a complete dataset composed of 11298 samples, and this model does not undergo any pretraining.

In this model, we use some convolution modules to extract the features of satellite images. Each convolution module is constructed by stacking convolution, leaky rectified linear unit (ReLU), batch normalization and maximum pooling layers. Four such convolution modules are used. The partial structure of the previous model is shown in Fig. 3; this structure replaces ResNet18. Furthermore, NN1, used for processing longitude, latitude and elevation data, is replaced with an untrained three-layer FCN, and the NN2 structure remains unchanged. ReLUs are used in all activation functions. The relevant parameters of the previous model are shown in Table 2.

Model training: To reduce the overfitting risks faced by the proposed model and the previous model, in the data preprocessing stage, we employ data augmentation techniques, such as rotation, random clipping, and affine transformation, to increase the generalization capabilities of these deep neural networks.

In the training stage, we adopt the Optuna framework to optimize suitable hyperparameters, such as the batch size and learning rate. The adaptive moment estimation (Adam) optimizer is used to minimize the loss function. Here, the two models employ the mean squared error (MSE) as the loss function. The validation set is predicted after each epoch of training. The changes observed in the MSE during training and testing are shown in Fig. 4. To observe these fluctuations more intuitively, the MSE values are standardized. It can be found that the deviation between the training error and the testing error lies within the acceptable range.

Simulation results: Two models are used to predict the field strength values, and the corresponding MSE, root mean square error (RMSE) and mean absolute error (MAE) values are obtained on the test set. The bar chart containing the error values of the two models is shown in Fig. 5. It can be found that the model with small sample data can achieve the same effects as those of the previous model in terms of these three indicators, and the error slightly decreases. The distributions of the predicted values and the measured data provided by the two models are shown in Fig. 6. The fitting effects of the two methods are good from the visual point of view. The results show that the prediction accuracy of the proposed method can reach that of the previous model in experiments. Although the test performance of the model is not greatly improved, the requirement of the new model regarding the number of data samples is significantly reduced. We use 11,298 data samples for the training, validation and testing of the previous model and finally obtain good results. However, in the newly proposed model, we only use a small part of the dataset (1,573 sample data) to achieve the same experimental effect. Therefore, it can be concluded that under small data samples, our new model can obtain a prediction accuracy that is not inferior to that of the previous

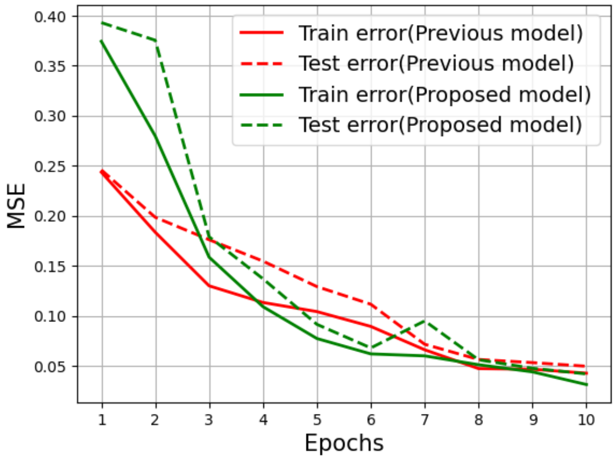


Fig 4 *MSE changes during training and testing (the MSE values are standardized for ease of observation).*

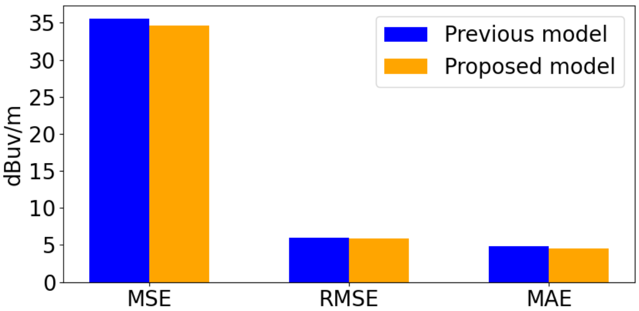
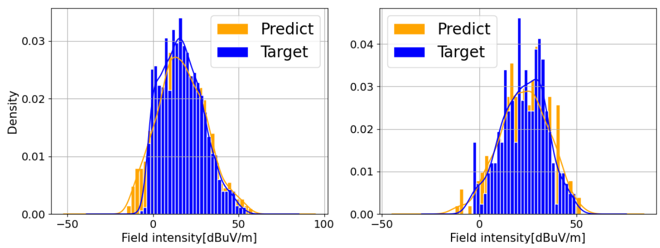


Fig 5 *The MSE, RMSE and MAE values of two different models are compared.*



(a) Previous model (b) Proposed model

Fig 6 *The distribution of predicted values and measured data for the two models.*

model with sufficient data samples.

Conclusion: In this work, we propose a field strength prediction model based on a deep neural network, which is used to accurately predict the field strength in a study area possessing few sample data. We connect two pretraining submodels to minimize the number of parameters to be learned. Compared with the previous model, our proposed model can achieve similar performance with less data. Therefore, our model can solve the problem that it is difficult to accurately predict radio wave propagation in cases with insufficient sample data. Additionally, this work enriches radio wave propagation prediction methods and improves the efficiency of wireless network planning and optimization.

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