A Comprehensive Survey of Machine Learning Based Pathloss Models for Wireless Communication Systems

Awal Halifa [1], Emmanuel Affum Ampomah [2], Kwame Oteng Gyasi [3], Kwame Opuni-Boachie Obour Agyekum [4], Kingsford Sarkodie Obeng Kwakye [5], Justice Owusu Agyeman [6], and Mubarak Sani Ellis [7]

[1, 2, 3, 4, 5, 6, 7] *Department of Telecommunication Engineering,*
Kwame Nkrumah University of Science & Technology, Kumasi, Ghana

Abstract:- With the advent of 5G networks and advancements in wireless communication, the need for adaptive and robust path loss prediction models has become increasingly critical. Although traditional empirical and deterministic models have served as foundational tools, they often fail to effectively capture the intricacies of modern wireless propagation environments. This shortfall has spurred a transition toward machine learning (ML) and deep learning (DL) techniques, which demonstrate greater adaptability across varying scenarios and frequency ranges.

This paper provides a comprehensive review of existing path loss prediction methods, focusing on the potential of ML and DL approaches as viable alternatives to conventional models. It explores a range of methodologies, from shallow algorithms such as Random Forest, Gradient Boosting, Support Vector Regression, and Artificial Neural Networks to advanced approaches like Convolutional Neural Networks, hybrid deep learning frameworks, and Adaptive Neuro-Fuzzy Inference Systems. By analyzing their performance, advantages, and limitations, the study identifies key trends and uncovers research gaps in this evolving field.

The findings aim to inform future research efforts aimed at designing path loss prediction models that are more accurate, efficient, and capable of adapting to the demands of next-generation wireless communication systems.

Keywords: *5G wireless communication systems, Artificial neural network, Deep learning, Feature engineering, Machine learning Algorithms, Pathloss prediction.*

1. Introduction

To effectively build and optimize wireless communication networks to satisfy user expectations, particularly for 5G networks, it is imperative to understand the propagation of radio waves. A crucial metric that characterizes the decrease in signal strength when a signal moves over a medium is path loss (PL) modeling [1]. Throughout the years, diverse path loss models have been formulated to cater to different scenarios, falling into categories such as theoretical or physical, deterministic, and empirical. However, their foundation was established using traditional statistical techniques, which have been shown to be unstable with a variety of wireless channels and prone to high prediction errors, particularly when tested outside the model's original environment [2]. For determining radio coverage and optimizing overall network efficiency, it is essential to employ models that can precisely and effectively estimate path loss (PL). Machine-learning-based PL models have emerged as efficient techniques addressing the limitations of traditional models used for evaluating radio-wave propagation and constructing channel models based on measurement data. To automatically approximate nonlinear systems, they can comprehend the structural relationships between data in complex settings [3].

This survey aims to comprehensively review and categorize the existing literature on machine learning-based path loss models. The survey covers a wide range of ML approaches, including supervised and unsupervised learning, deep learning, and ensemble methods, among others. We delve into each category, considering its relevance, advantages, and possible obstacles within the framework of path loss modeling for wireless communication systems.

The structure of this survey is outlined as follows: Section II offers an overview of radio propagation and path loss, emphasizing their limitations and advocating for the integration of machine learning. Section III introduces the fundamental principles of machine learning and its pertinence to wireless communication. Subsequent sections explore specific types of machine learning-based path loss models, delving into their methodologies, applications, and significant contributions. Finally, Section VI wraps up the survey by summarizing key insights and suggesting potential directions for future research.

As we progress through this survey, it becomes clear that the fusion of machine learning and path loss modeling holds significant potential for enhancing the capabilities of wireless systems, ultimately contributing to the establishment of more efficient, dependable, and future-proof networks.

2. Radio Signal Propagation: Journey From Transmitter to Receiver

A. Radio Propagation

In essence, radio-wave propagation involves the interaction between a transmitter and a receiver. Each endpoint comprises a receiver linked to an antenna characterized by specific geometry. Signals generated by the receiver undergo modulation through a carrier signal, and as the modulated signal traverses toward the receiver, it is demodulated at a speed primarily determined by the speed of light. The transmitted signal may experience attenuation and/or distortion due to environmental factors such as absorption, reflection, refraction, diffraction, or a combination of these processes. Proximity of obstacles to the line of sight (LOS) path can obstruct the Fresnel zone, leading to fading in received signal strength, presenting potential challenges. Furthermore, when multiple antennas release signals simultaneously at the same frequency and time but in different directions, complications arise. These signals may choose several routes to the recipient, resulting in various ways for each path to interact with its environment. Such signals are delayed by a certain amount when they reach the receiver. Constructive interference occurs when delays lead to signals that are in phase with each other. However, if the signals are out of phase, they will generate destructive interference. Multipath fading is the name given to the effects of this interference. We refer to the attenuation brought on by huge static impediments, such as buildings and mountains, as large-scale fading, shadowing, or slow fading. If the diminution results from small, temporary objects that evolve over time, it is referred to as small-scale fading. Doppler spreading can cause a frequency shift for mobile receivers. Frequency shifts and delays lead to small-scale fading [4].

B. Pathloss

The design and enhancement of wireless communication networks necessitate the inclusion of path loss prediction in the planning and optimization process. By considering variables including distance, frequency, topography, antenna height, and environmental characteristics, it includes predicting the attenuation of signal power as it propagates via the wireless medium. A straightforward, all-encompassing model for trail loss is needed for link budgeting, system performance optimization, coverage forecast, and an associate degree of accuracy.

Consequently, researchers and engineers have been diligently working on designing efficient and cost-effective algorithms for predicting path loss across different scenarios and frequency ranges [5]. In their research paper, [6] described their findings regarding path loss and how to predict it using machine learning. They stated that path loss is a change in a radio wave's power as it passes through a building between the transmitter and receiver. In wireless communication network design and development, path loss prediction holds significance, particularly as receivers require a minimum power level for accurate data reception. This is crucial for tasks such as link budget determination, coverage analysis, and base station placement. Several existing route loss models adopt a linear relationship between distance and path loss. By comparing graphical representations of the data, this approach has effectively addressed the issue [7].

In the study conducted by [8], an elucidation of path loss was provided by highlighting the fact that propagation models incorporate signal attenuation or path loss as a quantification of the electromagnetic wave's power density while traversing space from a transmitter. Path loss can be used to monitor network planning, coverage, and system performance to provide the best possible reception. Numerous factors, like as geography, frequency, and the elevations of both the transmitting and receiving antennas, can affect how far a signal can travel [9].

With a transmission power of P_{tx} Watts (W) and an antenna gain of G_t dBi, the overall Effective Isotropic Radiated Power (EIRP) from the transmitter's radio can be calculated as $P_{tx} * G_{tx}$. In logarithmic terms, P_{tx} is expressed in dBm, denoting decibels relative to a milliwatt, and the EIRP simplifies to the sum of P_{tx} and G_{tx}. Employing the standard log-domain link budget equation, the entire radio link can be succinctly summarized.

$$P_{rx} = P_{tx} + G_{tx} + G_{rx} - PL \tag{1}$$

using P_{rx} and G_{rx} to denote the power received by the receiver and the antenna gain of the receiver facing the transmitter, respectively. In this context, all attenuation due to path loss is encompassed within the PL term. This formula accounts for the combined gain and attenuation associated with multiple competing signals. Additionally, it assumes that there are no outside noise sources in the vicinity, such as thermal noise or transmitter interference. The ratio of signal to noise, expressed in the log domain as $\mathrm{SNR} = P_{rx} - \mathrm{N}$, frequently employed to depict signal quality at a specific location. The Signal to Interference and Noise Ratio (SINR) is alternatively defined considering interference arising from a recognized group of interfering sources:

$$\mathrm{SINR} = P_{rx} - \left(\mathrm{N} + \textstyle\sum_j^N I_j \right) \tag{2}$$

In the context of a specific receiver design and modulation system, there exists a known relationship between Signal-to-Noise Ratio (SNR) and bit error rate. This relationship, denoted as MDS (P_e) where P_e represents the probability of bit error, enables the determination of the minimum detectable signal for a given radio based on the acceptable error rate. Identifying the covered points becomes a straightforward process by considering the set of receiver locations that satisfy this inequality:

$$P_{tx} + G_{tx} + G_{rx} - PL \geq MDS(P_e) \tag{3}$$

Forecasting the PL value becomes intricate when considering the environment and the radio link, as the specific values of P and G are known for a given link. Conversely, in measurement-based approaches, the challenge lies in estimating the PL value for unmeasured locations through interpolation. In the context defined here, the model's objective is to predict the value of $L_t + L_s$ in this logarithmic domain equation:

$$PL = L_t + L_s + L_f(t) \tag{4}$$

L_s denotes the attenuation due to shadowing, arising from large stationary structures like buildings and mountains. L_t represents the fundamental free-space path loss, and L_ft signifies the short-term fast fading attributed to destructive interference from small scatterers and the impact of multipath effects, which exhibit variations over time (t). Time and frequency selectivity characterise small-scale fading, which means that it changes with time and frequency. It is not possible to expect models to anticipate the number L_f (t) without comprehensive knowledge of the environment. This additional error is commonly determined through a stochastic calculation involving a probability distribution, typically employing the Raleigh distribution, although the Ricean and m-Nakagami distributions are also frequently used. Thus, making it possible to model, if not precisely anticipate, frequency and time selective fades, which in turn enables the examination of their impact on modulation schemes [10][11]

The many approaches put out to forecast the distribution of $L_f(t)$ and the value of $L_t + L_s$ will be covered in the sections that follow.

3. Machine Learning Algorithms

This section exclusively addresses the commonly employed methods for predicting path loss in communication systems. Random Forest, ANN, and SVM are examples of shallow algorithms, whereas CNN is covered from a deep learning perspective. To the extent that the survey is self-contained, it provides readers with an understanding of the fundamental ideas behind these algorithms.

A. Random Forest Regressor (RFR)

The ensemble learning technique known as the Random forest (RF) consists of several regression trees[12]. A voting mechanism is used to improve each tree's prediction performance, helping to compensate for its weak robustness. Breiman and Cutler [13] proposed the unique non-parametric supervised machine learning technique known as Random Forest.

The bagging method called RF has its roots in "bootstrap aggregation". The main idea behind bagging is to take a dataset, bag a decision tree or other weak learner on it, and then make many bootstrap replicas of the dataset and use those to build decision trees. Each tree is given a different set of training data using Bootstrap aggregating. The ultimate outcome is ascertained by averaging the performance of every single tree, following the training process utilising these samples.

For reducing dataset redundancy or dimensionality, the RF is still a helpful technique. High dimensional input characteristic datasets provide more information, but the prediction accuracy may be lowered by superfluous and redundant components. In this study, the RF technique was used to process the observed signal dataset in order to extract the most relevant features and eliminate the superfluous and unimportant ones. Before applying the RF algorithms for regression analysis or data training, two or more of their primary hyperparameters must be provided [14]. One such hyperparameter is the quantity of trees. The subsequent section furnishes a mathematical elucidation of the RF input-output function model.

$$RF(x_n, y_n) = \{ f(x_n, \theta_m, y_n) \} \tag{5}$$

Here, θ_m represents the count of trees, and x_n, y_n denote the input and target output data, respectively. In this case, the endeavour to select the most valuable and informative subset of features was completed by employing a set of trees (200) on the targeted measured signal datasets.

B. Support Vector Regression (SVR)

The support vector machine (SVM) is a machine learning approach rooted in statistical learning theory. It operates by transforming a dataset nonlinearly from a fixed-dimensional space to a sophisticated-dimensional one, allowing for linear separation into distinct segments. SVR, a flexibility of SVM tailored for regression challenges, enables path loss prediction [15]. The primary goal of SVR is to identify a hyperplane within the high-dimensional feature space and align the sample points onto it. This hyperplane in the feature space can be defined by the linear function as follows.

$$f(\boldsymbol{x}) = w^T \varphi(\boldsymbol{x}) + b \tag{6}$$

where **x** is an input feature vector, w is the normal vector that controls the orientation of the hyperplane, $\varphi(\cdot)$ is the nonlinear mapping function, and b is the displacement item.

The ideal hyperplane is a constrained optimization problem of the form [16]

$$\min_{\boldsymbol{w}, b, \xi, \xi^*} \frac{1}{2}\boldsymbol{w}^T\boldsymbol{w} + C\sum_{i=1}^{N}(\xi_i + \xi_i^*) \tag{7}$$

$$s.t. f(x_i) - y_i \le \varepsilon + \xi_i \tag{8}$$

$$y_i - f(x_i) \le \varepsilon + \xi_i^* \tag{9}$$

$$\xi_i, \xi_i^* \ge 0, i = 1, \dots, N \tag{10}$$

where C denotes the regularization coefficient, ε represents the insensitive loss, signifying that the predicted value is considered accurate when the deviation between the predicted value and the actual value is less than ε, ξ_i, ξ_i^*

are slack variables that enable a slight variation in the insensitivity range on both sides of the hyperplane. Subsequently, by introducing Lagrange multipliers and solving the dual problem, the approximate function can be formulated as.

$$f\ (x)\ =\ \sum_{i=1}^{N}(-\alpha_i\ +\ \alpha_i{}^*)K(x_i\ ,x)\ +\ b \tag{11}$$

represent Lagrange multipliers, and K (·, ·) denotes a kernel function utilized for nonlinear mapping from a low-dimensional space to a high-dimensional space.

The performance of the SVR-based predictor is influenced by the selected kernel function. Currently prevalent kernel functions include the sigmoid, linear, polynomial, Gaussian radial basis function, and various combinations of these. In this study, a Gaussian kernel with adjustable parameters is employed as the kernel function, and it is defined as:

$$K(x_i, x_j) = \exp\left(-\gamma\ \left||x_i - x_j|\right|^2\right), \gamma > 0 \tag{12}$$

The Gaussian kernel is a widely used kernel function that performs effectively in tasks requiring no previous information and limited feature dimensions [17]. The same method employed in [20] was utilized to look up the parameters used in this investigation, including the regularization coefficient, insensitive loss, and kernel function parameter.

C. Artificial Neural Network

Artificial Neural Network (ANN) emerges as a favoured method for path loss prediction due to its capability to address nonlinear regression challenges and exhibit low prediction errors, particularly with large sample sizes [18] . ANNs are constructed by connecting neurons to form networks. The multi-layer perceptron structure of a feed-forward ANN, based on the neuron model, typically includes an input layer, one or more hidden layers, and an output layer. It is noteworthy that neurons within the same layer lack connections, and there are no cross-layer connections; however, neurons in the subsequent layer are fully interconnected with those in the current layer through different weights.

The precision and intricacy of the model are significantly influenced by the network scale, determined by the number of neurons and hidden layers. However, identifying the optimal ANN structure for path loss prediction remains a challenge. In a typical rural macrocell radio network planning scenario, research in [19] indicates that a less intricate ANN, such as a single-hidden-layer feed-forward ANN with a limited number of neurons, is likely to yield satisfactory accuracy in path loss prediction. In comparison, ANNs featuring multiple neurons and hidden layers may exhibit inferior generalization properties. The potential source of this problem is likely overtraining, where a model excels on data similar to the training dataset but lacks adaptability to handle variations.

ANNs are typically trained using the low-complexity back propagation approach. A common name for this kind of network is BPNN. With a collection of training samples represented as $\{(x_1, y_1), (x_2, y_2),\ \ldots, (x_N, y_N)\}$,where $x_i\ = \{x_1{}^i\ , x_2{}^i\ , \ldots, x_L{}^i\} \in \boldsymbol{R}^L$ is a feature vector and $y_i \in \mathbb{R}^1$ is the target result of path loss, the forward propagation stage computes the predicted path loss value, denoted as:

$$y_i{}'\ =\ f_o\ (\omega_{om}\ (f_m\ (\omega_{ml} x_i)\ +\ \theta_m))\ +\ \theta_o \tag{13}$$

ω_{ml} denotes the connection weights linking the hidden layer neurons to inputs, ω_{om} signifies the connection weights between the output layer neurons and the hidden layer, while θ_m and θ_o serve as the thresholds for the hidden layer neurons and the output layer neuron, respectively. Additionally, $f_m(\cdot)$ and $f_o(\cdot)$ represent the transfer functions corresponding to the hidden layer neurons and the output layer neuron, respectively.

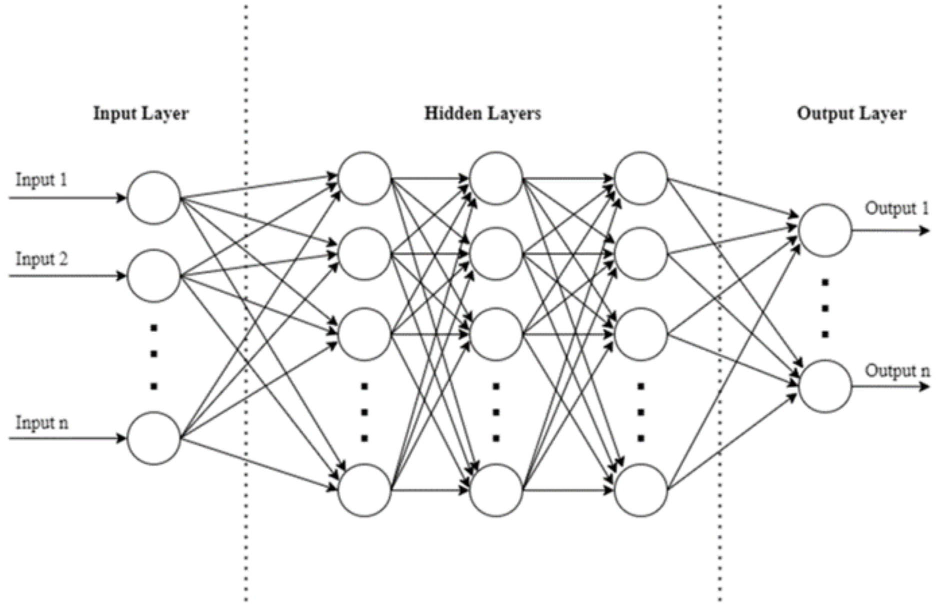

Fig. 1. A typical ANN architecture.

Assessing the generality capability of these Path Loss models based on Machine Learning, which involves gauging the prediction accuracy concerning the target values in both training and validation datasets, can be proficiently achieved using mathematical expressions. Metrics such as the mean absolute percentage error (MAPE), error standard deviation (ESD), mean absolute error (MAE), and root mean square error (RMSE), as depicted in the equations below, serve as effective tools for this evaluation.

$$MAE = \frac{1}{Q} \sum_{q=1}^{Q} \left| PL_q - PL'_q \right| \tag{14}$$

$$MAPE = \frac{100}{Q} \sum_{q=1}^{Q} \left| \frac{PL_q - PL'_q}{PL_q} \right| \tag{15}$$

$$RMSE = \sqrt{\frac{1}{Q} \sum_{q=1}^{Q} \left(PL_q - PL'_q \right)^2} \tag{16}$$

$$ESD = \sqrt{\frac{1}{Q-1} \sum_{q=1}^{Q} \left(PL_q - PL'_q \right)^2} \tag{17}$$

$$MaxPE = \max\left(PL_q - PL'_q \right) \tag{18}$$

Here, for the test sample index represented by $q = 1, \ldots, Q$, where Q is the total number of test samples, PL_q and PL'_q denote the samples from measurement and path loss, respectively.

D. Convolutional Neural Networks (CNN)

Within the domain of deep learning, Convolutional Neural Networks (CNNs) constitute a specific category of Artificial Neural Networks (ANNs), specifically tailored for tasks related to visual imagery. These networks emerged due to the limitations of traditional ANNs in handling complex computations related to image data. The origins of CNNs draw inspiration from the visual system of animals, notably the pioneering work of Hubel and Wiesel in 1959. They observed that cells in the animal visual cortex can discern light within small receptive fields. This discovery influenced the creation of CNN models and architectures [20].

Building on these discoveries, LeCun et al. introduced the modern CNN framework, exemplified by LeNet-5, renowned for recognizing handwritten digits using a backpropagation algorithm for training [21]. Despite the advancements, the need for more robust and innovative approaches persisted. The breakthrough came with the introduction of AlexNet by Krizhevsky et al. in 2012. This model not only garnered attention but also paved the way for modern CNN architectures, applicable in both computer vision and natural language processing [22].

Typically, a CNN comprises one or more blocks of convolutional and pooling layers, followed by fully connected (FC) layers and an output layer. The convolutional layer, a fundamental building block, learns feature representations from inputs through the use of learnable convolutional kernels or filters, generating various feature maps [23]. CNNs distinguish themselves from other pattern recognition algorithms by seamlessly integrating both feature extraction and classification [24]. Fig. 3 illustrates a basic CNN through a simplified schematic representation. This uncomplicated network comprises five distinct layers: an input layer, a convolution layer, a pooling layer, a fully-connected layer, and an output layer. These layers are bifurcated into two segments: feature extraction and classification. Feature extraction entails an input layer, a convolution layer, and a pooling layer, while classification involves a fully-connected layer and an output layer.

The input layer establishes a fixed size for input images, which may be resized as necessary. Subsequently, the image undergoes convolution with multiple learned kernels utilizing shared weights in the convolution layer. Following this, the pooling layer reduces the image size while endeavoring to retain pertinent information. The outcomes of the feature extraction process are termed feature maps. The classification phase amalgamates the extracted features within the fully-connected layers. Lastly, each object category in the output layer is represented by a dedicated output neuron. The result of the classification phase culminates in the classification outcome.

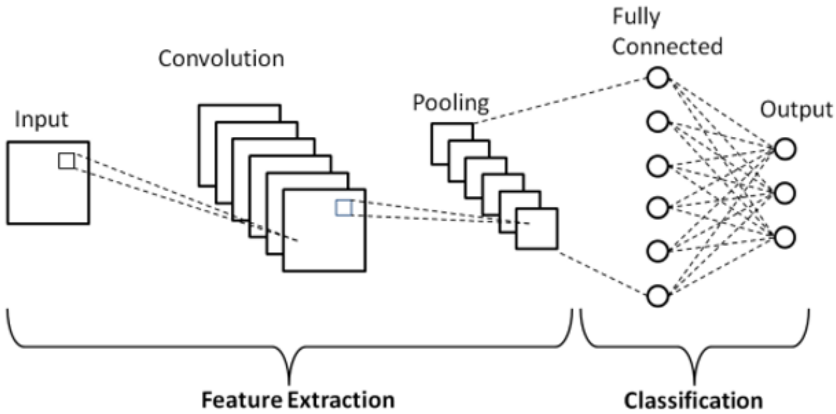

Fig. 2. Fundamental architecture of a convolutional neural network (CNN) [25].

4. Machine Learning Modeling of Pathloss

To obtain approximated functions for path loss, one might apply the machine learning idea. A supervised learning approach is usually used for path loss prediction. In order to forecast path loss, modelling requires input features as well as output. The machine learning algorithm computes a function that corresponds to the output. The initial stage involves collecting data, where measurement samples are acquired, encompassing both the path loss value and its associated attributes. These attributes are classified into two classes: system parameters and environmental parameters. System-dependent parameters include antenna separation distance, height, transmitter and receiver positions, angle between line of sight and the horizontal plane, carrier frequency, and other relevant factors. The propagation of the environment has no bearing on these factors. Terrain, vegetation, and building conditions are examples of environment-dependent parameters that are influenced by local weather and environmental factors [26]. Temperature, precipitation rate, humidity, and other variables are derived from the weather. The path loss prediction model's performance is strongly correlated with the sample data size. Practically speaking, the data gathered from the measurement include hundreds of features, including parameters that are undesired and unnecessary. The algorithm's ability to model the path loss for prediction is often negatively impacted by the irrelevant parameters. In order to decrease the quantity of features without sacrificing their quality, feature selection is used. The most pertinent subset features with the data needed to forecast the path loss are chosen through feature selection. There are several feature selection techniques, including wrapper, filter, and embedding.

Following feature selection, an apt procedure for modelling the PL for prediction is selected or adjusted. The algorithm's accuracy and complexity are among the elements considered when choosing the right one. The algorithms' hyperparameter values are established prior to the start of the learning process. There are several methods for choosing the ideal set of parameters, including grid search, random search, and Bayesian optimisation. The effectiveness of hyperparameters significantly impacts the competence of algorithms in predicting path loss. The algorithm's efficacy and efficiency are determined by measuring the performance. Evaluation metrics encompass mean absolute error, mean absolute percentage error, maximum prediction error, correlation factor, root mean square error, and error standard deviation [27]. But since there aren't any performance measurements that are accepted by all research groups, different studies employ various performance metrics.

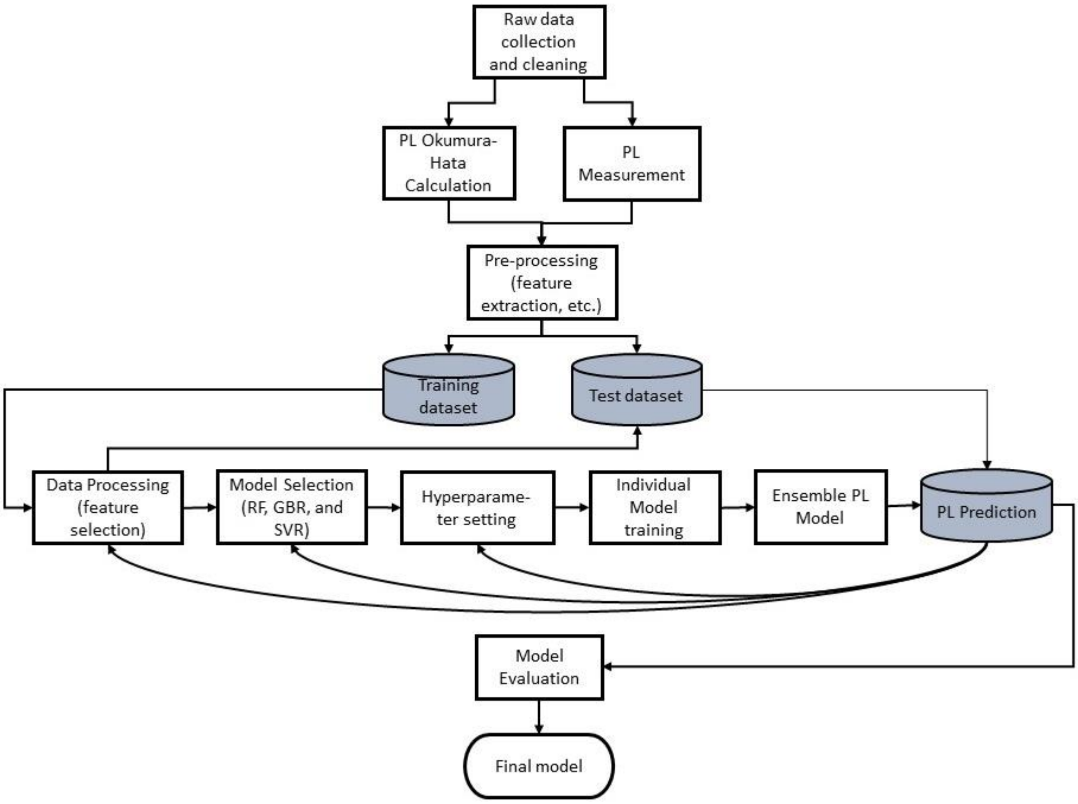

Fig. 3. The process of conducting path loss analysis using machine learning techniques

A. Comparison of traditional and machine learning methods

It is possible to summarise the contrast between these two methods for forecasting path loss in wireless signal broadcast by pointing out that they are all concerned with doing so, but in slightly different ways. For example, conventional methods are often considered a priori, meaning that they rely on past environmental knowledge to forecast future transmission events by employing precise measurements. In contrast, machine-learning techniques use data inputs and outputs to create or develop models. Path loss data features are picked or retrieved from input data using models that are designed to take transmission data inputs [28]. To arrive at an informed decision regarding propagation path loss, machine learning models utilize their predictive capabilities by analyzing the attributes extracted or selected from input data. When facing challenges or impossibilities in undertaking such tasks, machine learning methods are specifically suited to handle these situations [29]. The key advantage of the machine learning technique lies in its ability to create a model, train it based on desired outputs, and validate it against real-world scenarios. This fundamental feature distinguishes machine learning from traditional models, enhancing its predictive accuracy. Additionally, in scenarios where prior knowledge of the environment is lacking, machine learning can still offer predictions based on environmental variables, yielding results more accurate than those obtained through conventional methods [30].

Given the constant variations in the propagation environment, it becomes imperative to equip generated models with the accurate parameter set for evaluating the efficacy of machine learning in path loss prediction. Hence, ensuring appropriate feature selection and extraction is crucial to yield significant results in effective path loss prediction, validated through performance testing. This underscores a key advantage of the machine learning technique over the traditional approach [31]. In contrast to the conventional propagation path loss method, which relies on predicting for a single path or a set of comparable paths, machine learning algorithms can anticipate propagation path loss across diverse locations. Furthermore, the machine learning approach not only establishes a connection between input and output data but also has the capability to make predictions based on both labelled and unlabelled data[32].

The classical approach holds a significant advantage in predicting propagation path loss in scenarios where conducting measurements is either practically infeasible or presents challenges, distinguishing it from the machine learning approach [33]. Even if the traditional model approach's correctness is sometimes disputed or called into doubt, it is nevertheless relatively straightforward to comprehend and apply, which facilitates its incorporation into a number of network simulators. Yet, an additional limitation of traditional techniques lies in their capability to predict propagation path loss solely along a single trajectory, adjusting solely based on the data at their disposal from one or more specific environments. These classical models rely on inputs such as distance, carrier frequency, and the heights of both the transmitter and receiver. The conventional approach allows for supplementary models that, while potentially unable to operate independently, have the potential to enhance existing, less effective models, rendering them more attractive.

B. Predictive Model for Path Loss Using Deep Learning

Deep learning architectures extensively utilized for path-loss prediction encompass CNNs and hybrid models. These hybrid models amalgamate two or more diverse deep learning algorithms, such as combining shallow algorithms with deep learning or integrating traditional techniques with deep learning. The incorporation of these approaches enhances the accuracy of path-loss predictions.

C. Pathloss prediction on convolutional neural network

In wireless communication networks, the CNN and its variations are used to anticipate route loss. CNN architectures are utilized by[34]. Research in [35] predicts outdoor path loss from 2D satellite pictures using a transfer learning VGG-16 model, while [36] predict interior 5G communication path loss using a CNN equipped with meta-learning. While the latter emphasizes how the meta-learning technique outperforms traditional CNN and empirical models in indoor situations, the former underlines the advantage of VGG-16 over ray tracing. Although [37] emphasis on meta-learning for 5G scenarios and [38] focus on outdoor surroundings both improve accuracy in their respective contexts, these are the main differences between the two research.

For different contexts, Cheng et al.[39], Levie et al.[40], and Nobuaki et al.[41] offer different CNN-based path loss prediction models. In suburban regions, Cheng's model handles 28 GHz mmWave route loss, outperforming deterministic and empirical models in terms of complexity and accuracy. In contrast to models employing radial basis functional interpolation and tensor completion techniques, Levie's RadioUNet model for cellular optimization makes use of numerous input channels to build desirable radio maps. However, in contrast to ray tracing, Nobuaki's AlexNet model improves estimation accuracy by taking reflection and diffraction into account in open situations. Although Levie's contribution is in the area of cellular optimization, Cheng and Nobuaki concentrate on particular outside circumstances, demonstrating the variety of applications.

In a variety of communication systems, Ma et al.[42], Kuno et al. [43], and Qiu et al. [44] use CNNs to anticipate path loss. Ma's CNN-based model outperforms 3D ray tracing methods in indoor Wi-Fi path loss prediction. CNNs are used in Kuno's model for prediction, with a focus on the significance of creating top and side view images for route loss modelling. Modern 3D ray tracing simulators can attain similar accuracy levels as Qiu's PP-Net, but with far more processing efficiency. Although Qiu's work stands out for its efficiency advantages, Ma and Kuno concentrate on specific communication scenarios (general communication and indoor Wi-Fi, respectively), while Qiu offers a trade-off between computing complexity and accuracy.

While Sotiroudis et al. [45] and Bal et al. [46] both use CNNs for path loss prediction, their methods are different. Bal shows that path loss may be predicted in certain areas by using VGG-16 to extract image features from height maps and satellite images that are peculiar to a given region. As opposed to tabular data, Sotiroudis use CNNs for path loss prediction in urban settings, associating a picture with each measurement and demonstrating flexibility to novel surroundings with reduced computing complexity. Bal's research focuses more on region-specific forecasts, but Sotiroudis shows how flexible and effective CNNs can be in city environments.

Table I. Overview of CNN-Based Path Loss Prediction

Ref	Deep Learning Architecture	Baseline Algorithms	Indoor / Outdoor	Generation	Results
[3]	Transfer learning VGG-16	Ray Tracing	Outdoor	Not specified	Improved accuracy of path-loss prediction using VGG-16
[47]	Meta-learning-configured CNN	Conventional CNN, Empirical models	Indoor	5G	Outperforms conventional CNN and empirical models in path loss prediction through meta-learning configuration.
[48]	RadioUNet	Radial basis functional interpolation, Tensor completion	Not specified	Not stated	Outperforms models based on radial basis functional interpolation and tensor completion in cellular optimization and device-to-device link scheduling.
[49]	CNN	Empirical, Deterministic models	Outdoor (suburban)	5G	Proposed model excels in accuracy and complexity compared to empirical and deterministic models in 28 GHz mmWave path loss prediction.
[50]	AlexNet	Ray tracing	Outdoor (open)	Not stated	Enhanced path loss estimation accuracy compared to ray tracing in open environments.
[51]	CNN	Conventional model and CNN model	Not specified	Not Available	CNN outperforms conventional models in predicting path loss using building side view and top view images.
[52]	CNN	3D ray tracing methods	Indoor	Not specified	CNN performs better than 3D ray tracing methods in indoor Wi-Fi path loss prediction.
[47]	Path loss prediction network (PP-Net)	State-of-the-art 3D ray tracing simulator	Outdoor	5G	PP-Net's accuracy is comparable to 3D ray tracing simulator but is 30 times faster.

Ref	Deep Learning Architecture	Baseline Algorithms	Indoor / Outdoor	Generation	Results
[53]	VGG-16	None mentioned	Not specified	Not Available	Region's satellite image or height map can be used to predict path loss.
[54]	CNN	Tabular data	Outdoor (urban)	Not Available	CNN produces similar results with tabular data and adapts swiftly to new environments with less computational complexity.

1) Pathloss Prediction with Hybrid Deep Learning

This section delves into the utilization of hybridized deep learning techniques for predicting path loss in wireless communication systems. Thrane et al. [55] and Sotiroudis et al. [56]use a hybrid deep learning strategy that combines CNN with additional algorithms (ANN and XGBoost, respectively). While Sotiroudis' CNN-XGBoost surpasses other hybrid algorithms in 5G and IoT situations by merging tabular data and images, Thrane's ANN-CNN hybrid improves accuracy in mobile communication systems using satellite photos. In addition, Lee et al [57] demonstrates enhanced performance over deterministic models and probabilistic predictions when using CNN hybrids (3D ray tracing-CNN and CNN-NGBoost, respectively) for outdoor millimetre wave channels and urban environments.

Ates et al. [44] and Juang [45] investigate various hybrid models. Juang's AE-GAN outperforms traditional models at 3.5 GHz in translating street map imagery for PL prediction.

In contrast to ray tracing, Ates et al.'s VGG-16-ResNet-50 exhibits proficient accuracy in predicting path loss exponent and shadowing factor using 2D satellite imagery. Sani et al.[46] introduce a ResNet50V2-regression hybrid capable of accommodating multiple factors and configurations, leading to highly accurate path loss predictions. Cheng et al.[47] propose an attention-enhanced CNN (AE-CNN) hybrid for millimeter-wave path loss in 5G. This model showcases its efficacy in 5G communication networks by surpassing deterministic and empirical methods through distance entrenched local range multi-scanning.

D. Shallow Algorithms for pathloss prediction

1) Forecasting Path Loss Using Adaptive Neuro-Fuzzy Inference System (ANFIS)

The table exhibits experiments illustrating the application of fuzzy logic models and the ANFIS for predicting path loss in wireless communication systems. In their work, [48] leveraged measured Received Signal Strength (RSS) data to develop a path loss prediction model based on ANFIS. The findings indicated that the ANFIS model yielded reduced errors, underscoring its reliability in predicting path loss for mobile communication systems in comparison to the, Okumura-Hata, and COST-231 model. In order to lower prediction errors, [49] developed a hybrid approach that combines fuzzy logic with k-means clustering. The model simultaneously used multiple path loss prediction algorithms and region topographical variability. When compared to drive-test measurement data, the k-means fuzzy scheme demonstrated a decreased prediction error of 2.67%, demonstrating a considerable improvement over conventional model.

To predict path loss in LTE-1.8 GHz networks, [50] employed a hybrid approach integrating ANN and Neuro-Fuzzy logic. The research utilized GPS measurements and cellular signals, combining the shared attributes of fuzzy logic and artificial neural networks. The proposed models exhibited enhanced accuracy compared to established path loss prediction models like COST Hata, Ikegami-Walfisch, and ITU-R P1546-4. [51] utilized ANFIS to refine function approximation and model tuning for analyzing broadcast within metropolitan environments, particularly with buildings and structures. In comparison to the Bertoni-Walfisch model, the ANFIS model performed better, exhibiting lower errors and higher accuracy in urban propagation settings. [52] modified the Hata model for PL prediction by utilizing spline interpolation and fuzzy logic procedures. 65 offline trainings with several fuzzified inputs were used to train spline interpolation and, fuzzy logic was used to increase the model sensitivity. For the study region, the use of spline interpolation in conjunction with fuzzy logic reduced route loss by 1.94 dB.

[53] utilized the Adaptive Neuro-Fuzzy Inference System model, trained with received signal strength data, to investigate the broadcast of multi-transmitter radio waves. They conducted a comparative analysis between various empirical models, including Hata, Ericsson, COST-231, Egli, and ECC-33, against the proposed model. The ANFIS model yielded attributes essential for radio network planning, as indicated by the outcomes. Additionally, [54] introduced a fuzzy-logic approach for secure path loss forecast in cellular mobile networks. The propagation medium was classified into well-defined fuzzy sets by the fuzzy-logic model, which also worked with imprecise notions. The model performed better than the HATA model, demonstrating a notable variation in route loss rate and offering precise base station position predictions.

[55] presented a model for forecasting path loss data, combining artificial neural networks (ANN) and fuzzy logic. In this hybrid approach, fuzzy logic incorporated expert knowledge, while the neural network learned interference patterns. The Neuro-Fuzzy model demonstrated superior performance compared to their prior ANN model, thereby enhancing interference path loss modeling. [56], in contrast to Hata's empirical approach, employed a binary phase shift keying (BPSK) method with modulated signals, integrating fuzzy logic for path loss determination. The model, utilizing fuzzy logic, effectively predicted route loss in wireless systems across various signal variation regimes.

[57] introduced a fuzzy logic strategy for anticipating path loss in cellular mobile systems. The model categorized the broadcast routes into two environment densities, demonstrating superior path loss prediction performance compared to the conventional HATA model. Employing fuzzy logic, [58] identified unknown path loss in urban streets from a set of known values, enhancing the prediction of unfamiliar path loss compared to traditional multi-ray models. Additionally, [59] developed a multi-layer fuzzy logic-based system (MLFS) for forecasting mobile path loss in forested environments. This model, incorporating a supervisory layer and linguistic rules, outperformed traditional empirical mathematical models, providing accurate results for path loss slopes. Furthermore, [60] proposed a fuzzy linear regression model for path loss in forested areas, considering tree density impacts. The fuzzy regression model exhibited improved path loss prediction in forested regions, aligning more closely with observed data than traditional regression models.

[61] introduced a model based on ANFIS for estimating route loss in the VHF band. The optimized ANFIS model demonstrated superior performance, exhibiting the lowest Root Mean Square Error and Mean Error compared to widely used conventional models. [62] presented a fuzzy-logic model designed for predicting path loss in a metropolitan context. When trained with driving test data, this model surpassed traditional physical and empirical models like the Hata model and free space propagation model in terms of efficiency, speed, and accuracy. [63] proposed an ANFIS-based technique for predicting path loss in the extremely high-frequency band for multi-transmitter radio propagation. The comparison with empirical models, including HATA, COST 231, Egli, and ECC-33, demonstrated improved path loss prediction using the optimized five-network structure of ANFIS.

Table II. Hybrid Deep Learning Architecture Pathloss Prediction

Ref	Hybrid Deep Learning Architecture	Baseline Algorithms	Indoor / Outdoor	Generation	Results
[40]	ANN-CNN	Stochastic models, Ray-tracing methods	Not specified	5G	Hybrid model (ANN-CNN) improves path loss prediction accuracy compared to stochastic models and ray-tracing methods in mobile communication systems

Ref	Hybrid Deep Learning Architecture	Baseline Algorithms	Indoor / Outdoor	Generation	Results
[41]	CNN-XGBoost	Stacked generalization, Feature concatenation	Not specified	5G and IoT	CNN-XGBoost predicts path loss with higher accuracy compared to stacked generalization and feature concatenation in 5G and IoT communication systems
[42]	3D ray tracing-CNN	Deterministic Channel Models	Outdoor	5G	3D ray tracing Hybrid model (3D ray tracing-CNN) enhances path loss prediction compared to Deterministic Channel Models in outdoor millimeter wave channels
[43]	CNN-NGBoost	CNN	Not stated	Not stated	Hybrid model (CNN-NGBoost) predicts path loss with improved performance in probabilistic path loss prediction in urban environments
[45]	AE-GAN	Conventional models	Outdoor	5G	Hybrid model (AE-GAN) performs better than conventional models for path loss prediction at 3.5 GHz band
[44]	CGG-16-ResNet-50	Ray tracing	Not specified	Not stated	VGG-16-ResNet-50 predicts path loss exponent and shadowing factor with 88% and 77% accuracy, respectively, compared to ray tracing in wireless channel systems
[46]	ResNet50V2-regression	MLP deep learning models	Not stated	5G	Hybrid model (ResNet50V2-regression) accurately predicts path loss for multiple parameters and environments
[47]	AE-CNN	Empirical, Deterministic methods, and 3D ray tracing	Outdoor	5G	AE-CNN hybrid model outperforms state-of-the-art empirical and deterministic methods in millimeter wave path loss prediction for 5G communication network

Table III. Fuzzy Logic-Based Pathloss Prediction

Ref	Fuzzy Logic Model	Baseline algorithms	Environment	Generation	Results
[49]	Fuzzy Logic, K-Means Clustering	free space loss, Walfisch–Ikegami, HATA, ECC-33	Not specified	Not specified	When compared to traditional models, the accuracy of the path loss prediction was improved.
[48]	ANFIS	Free-space, Okumura-Hata, COST-231	Not specified	Not specified	Path loss prediction was improved and the model remained stable.
[50]	ANN, Neuro-Fuzzy Logic	COST 231-Hata, Ikegami-Walfisch, ITU-R P1546-4	Outdoor	4G	The techniques improved the network's path loss prediction.
[52]	Fuzzy Logic, Spline Interpolation	Hata model	Not specified	Not specified	the proposed model reduced path loss by 1.94dB
[51]	ANFIS	Bertoni-Walfisch	Urban areas	Not specified	prediction error was decreased
[53]	ANFIS	Hata, WI, SUI, Ericsson, COST-231, Egli, ECC-33	Not specified	Not specified	the model created proves positive and favourable attributes in predicting path loss
[55]	Modulated ANN, Fuzzy Logic	Previous ANN model	Not specified	Not specified	The model improved the prediction of interference-related path loss in airplane
[54]	Fuzzy Logic	HATA	Not specified	Not specified	The suggested model excels in predicting path loss when applied to an uncharted environment
[56]	BPSK	Hata's empirical formula	Not specified	Not specified	The model improved the prediction of path loss for different kinds of modulated signals
[58]	Fuzzy Logic	Multi-ray models'	Urban streets	Not specified	Fuzzy logic models provided a better prediction of path loss
[57]	Fuzzy Logic	Conventional HATA model	Not specified	Not specified	In terms of path loss prediction accuracy, the model performs better than the traditional HATA model.

Ref	Fuzzy Logic Model	Baseline algorithms	Environment	Generation	Results
[59]	Multi-layer Fuzzy Logic	Conventional empirical mathematical model	Not specified	Not specified	The fuzzy logic models provided better prediction accuracy of path loss
[61]	ANFIS	Hata, COST 231, Egli, ECC-33	Not specified	Not specified	Experimental results indicate the fitness of the proposed model for path loss prediction
[60]	Fuzzy Linear Regression	Conventional regression models of previous research	Forest areas	Not specified	When compared to traditional empirical models, the fuzzy logic technique yielded an accurate estimate of path loss.
[63]	ANFIS	HATA, COST 231, Egli, ECC-33	Not specified	Not specified	The proposed model shows higher accuracy and efficiency in propagation path loss prediction
[62]	Fuzzy Logic	Free space propagation model, Hata model	Metropolitan environment	Not specified	The proposed model was efficient, faster, and accurate in the prediction of propagation path loss

2) Pathloss Prediction Based on ANN

This section delves into studies employing Artificial Neural Networks (ANN) for predicting path losses in wireless communication systems. [64] proposed a multilayer perception ANN to forecast path loss, precisely predicting route loss for a wireless network. Principal Component Analysis (PCA) was utilized to extract low-dimensional environmental aspects, integrating them with base station and receiver data. This model outperformed the $\alpha - \beta$ path loss model and Close-In Path loss model. [65] suggested a Back Propagation-ANN for radio wave propagation and route loss prediction, demonstrating improved accuracy over drive test data. [66] explored MLPNN and Radial Basis Function Neural Network (RBFNN) for path loss prediction in LTE networks. RBFNN outperformed MLPNN. [67] proposed a tripod machine learning framework involving PCA-based feature extraction, Gaussian process-based variance analysis, and ANN-based multi-dimensional regression, outperforming traditional models.

[68] compared ANN-based and fundamental models for route loss estimation, concluding that the ANN model outperformed Hata, Egli, COST-231, Ericsson model, and other empirical path loss models. [69] suggested an ANN-based multi-dimensional regression framework for path loss modeling in urban settings, surpassing traditional linear models. [70] compared ANN models in suburban and urban settings, revealing the ANN model's superiority over the COST-231-Walfisch-Ikegami model. [71] compared ANN with random forest for path loss modeling in NB-IoT networks, demonstrating equivalent performance.

[72] investigated ANN parameters for path loss prediction in very high-frequency wireless channels, showing ANN's superior prediction accuracy over Hata, COST 231, ECC-33, and Egli models. [73] conducted a comparative analysis of 60 GHz path loss channel modeling, favoring MLP over RBF. [8] proposed an ANN model for predicting macro cell path loss, surpassing ITU-R P.1546 and Okumura-Hata model. [77] forecasted path loss in a smart campus setting using ANN and random forest, enhancing prediction accuracy.

[29] adopted a four-model approach for machine learning path loss prediction in aircraft cabin conditions, demonstrating data expansion's efficacy. [79] presented a streamlined machine learning-based air-to-ground route loss modeling in urban settings. [80] characterized path loss for UAV-enabled communication in smart farming situations, employing ANNs and SVRs with high accuracy.

[76] investigated machine learning techniques for path loss prediction at 3.7 GHz in a rural setting, favoring ANN for its better prediction results. [77] explored machine learning models, including ANN and random forest, for path loss prediction in a smart campus setting. [78] compared path loss prediction using ANN and statistical models, revealing ANN's superior performance.

For aircraft cabin conditions, [29] suggested a four-model approach based on machine learning path loss prediction. To guarantee the dependability and stability of the wireless communication in the cabin, they looked into the factors of path loss. AdaBoost, Random Forest, Support Vector Regression (SVR), and BPNN were all used in the study. While the SVR handles non-linear regression issues, the BPNN models the linear relationship between inputs and outputs. Two random processes—feature selection and sample selection based on bagging—are managed by the random forest. Boosting algorithms, or AdaBoost methods, can be used on top of the base learner layer. It was discovered that the data expansion approach improved prediction performance with a small number of measurement samples at different frequencies. A streamlined machine learning-based air-to-ground route loss modeling for an urban setting was presented by [79]. The study included several recommendations for building an empirical route loss model for radio frequency communications from the air to the ground. They suggested several regression techniques, such as the ANN, KNN, and regression tree (RT). The GPS coordinates of ground receivers and transmitters for unmanned aerial vehicles (UAVs) were employed in the study. Through comparison with numerical findings, the proposed model's validity was confirmed. The study's findings indicate that the suggested approach enhanced path loss prediction. Path loss characterization machine learning methods for a ground sensor were presented by [80] for UAV-enabled communication in smart farming situations. They used ANNs and SVRs to measure data in various contexts. The suggested SVR and ANN models can best characterize path loss in a smart farming scenario, with corresponding accuracy of 95% for SVR and 97% for ANN, according to the findings of a comparison of their performance with the GUT-R model.

[70] compared ANN-based models for path loss prediction in an indoor setting using a multilayer perception and a generalized regression neural network (Radial Basis Function). We looked into prediction error, standard deviation, and root mean square error of the suggested network's performance. Measured data gathered in the 1890 MHz frequency was used to train the model. Experimental outcomes Results demonstrated that when compared to the empirical model with high accuracy, the model produced high accuracy.

For propagation path loss in a mining scenario, [81] presented an ultra-wide band (UWB) propagation channel model. The path loss attenuation change as a function of frequency and distance was the main emphasis of the model. Multiple experiments were conducted to confirm the validity of the model, which was trained using performance sufficiency. The model's accuracy in accurately predicting the received power levels was estimated as a means of testing the model. In the mine context, the suggested model generated good prediction accuracy when compared to empirical models based on experimental findings. Three methods are used in the machine learning framework [67] to predict path loss: PCA-aided feature extraction, Gaussian process-based variance analysis, and ANN-based multi-dimensional regression (ANN). In order to decrease the dataset's dimension, the researchers employed PCA for feature extraction. On the other hand, the Gaussian process was used to learn the shadowing effects, while the ANN learned the path loss structure from the dataset with reduced dimension. The findings of the study demonstrated that, when compared to traditional linear path loss models and log-normal shadowing models, the combined approach of the path loss model and shadowing model gave more flexible and accurate results.

An ultra-high frequency path loss model for heterogeneous networks utilizing a machine learning was proposed by [82]. Several elementary neurons spread over multiple layers comprised the MLPNN they projected. Using inputs from conventional propagation models, the proposed model is based on MLPNN, which used the backpropagation technique. In comparison to the ITU-R P.1812-4 and the Standard Propagation Model (SPM), the suggested model outperformed the other models and was able to forecast the path loss for heterogeneous networks with accuracy. Table 5 provides an overview of research that used ANN to forecast path loss in mobile wireless communication systems.

Table IV. Artificial Neural Network Based Pathloss Prediction

Ref	Model	Key features	Environment	Results
[64]	Multilayer Perception ANN	PCA for environmental feature extraction	Not specified	Outperformed Close-In Path loss model and α−β path loss model
[65]	Back Propagation-ANN	Minimization of drive test, grid division	Not specified	Accurate prediction with minimal cost
[66]	RBFNN and MLPNN	LTE networks, smartphone-based testing	Indoor	RBFNN outperformed MLPNN
[67]	ANN	ANN-based regression, Gaussian process, PCA	Not specified	Accurate path loss and shadowing modeling
[71]	Comparison of ANN and random forest	Path loss modeling in NB-IoT networks	Not specified	Similar performance between ANN and random forest
[72]	Various ANN architectures	VHF wireless channels, ECC-33, Egli, Hata, COST 231 models	Not specified	ANN-based prediction with better accuracy than traditional models
[73]	Comparative study of ANN and RBF	60 GHz path loss channel modeling in a mining environment	Mining site	MLP had less error compared to RBF
[8]	ANN for macro cell path loss prediction	Simple neuron model, feed-forward model	Not specified	The proposed model outperformed Okumura-Hata model and ITU-R P.1546
[68]	ANN	MLPNN parameters variation	Not specified	Outperformed basic empirical path loss models
[69]	ANN modeling for urban environment	Three-layer MLPNN, activation functions	Not specified	More accurate and flexible compared to linear models
[70]	MLPNN and Radial Basis Function	1890 MHz band	Indoor	High accuracy compared to empirical model
[81]	ANN	UWB propagation channel model	Mines	High prediction accuracy compared to empirical models
[29]	BPNN	Random Forest, AdaBoost, and Support Vector Regression	Aircraft cabin	Enhanced prediction performance with data expansion method
[79]	Regression algorithms including KNN, RT, ANN	Air-to-ground path loss modeling in urban environment	Outdoor	Improved path loss prediction

Ref	Model	Key features	Environment	Results
[80]	SVR and ANN	Ground sensor for UAV-enabled communication	Not specified	Optimally characterized path loss in smart farming scenarios
[74]	ANN	Log-distance and Cost 231-Hata	Not specified	Enhanced signal power path loss determination
[75]	ANN	SVM	Not specified	PCA-based prediction model produced better results
[76]	ANN, SVM, random forest, KNN	Extended Hata	Not specified	Outperformed empirical models and suggested ANN
[77]	ANN and random forest	COST-231 Hata	Not specified	Improved prediction accuracy compared to COST-231 Hata model
[78]	ANN	Comparison with Statistical model	Not specified	ANN performed better than mixture models
[82]	MLPNN	ITU-R P.1812-4 and Standard Propagation Model	Not specified	The suggested model outperformed ITU-R P.1812-4 and Standard Propagation Model

5. Future Research: Addressing Challenges and Adopting a Fresh Perspective

Numerous obstacles are encountered by existing path loss models, prompting exploration into a novel realm of path loss prediction facilitated by recent advancements in AI, robust deep learning structures, machine learning approaches, and computational intelligence methods. This section delves into several of these challenges, providing comprehensive coverage and suggesting avenues for future research in the field of path loss prediction.

A. Modelling with Deeplearning

Current investigations into path loss must thoroughly examine the various challenges encountered by deep learning models. One key challenge is the time-intensive nature of training a deep learning architecture; however, once trained, offline inferencing can be conducted swiftly and in real-time. Fortunately, recent advancements in graphics processing unit architecture and high-performance computing have significantly reduced deep learning model training times. Despite these improvements, the individual cost of acquiring such systems remains high. A viable alternative is the use of cloud-based infrastructure, where researchers have successfully trained and implemented robust deep learning solutions across diverse domains. This avenue holds promise for future path loss prediction modeling research.

While not a groundbreaking concept, it has been implemented in numerous studies. For instance, Thrane et al. [40] proposed a fusion of traditional artificial neural network (ANN) with convolutional neural network (CNN) – referred to as ANN-CNN – for predicting path loss in mobile communication systems based on input from satellite photos. In this architecture, the ANN computes numerical characteristics, while the CNN processes the satellite images. It was found that, in comparison to stochastic models and ray-tracing techniques, this architecture increased the path loss forecast accuracy. Which deep learning architecture offers the best performance for creating effective route loss predictive solutions is still a challenge for the path loss predictive modelling research community. In addition, the application of existing deep learning technologies should be reckoned with for the creation of precise PL prediction models for future technologies.

B. Feature Engineering

Finding discriminative features for the system's development is a crucial step in creating a path loss prediction model. There are two types of characteristics or parameters utilized in path loss modelling: environment features and system features. System attributes such as carrier frequency, antenna gains, transmitter and receiver heights, operating frequency, and the angle between the line of sight and the horizontal plane are contingent upon the specific system under consideration. These attributes, being independent of the environment, can be extracted autonomously. Conversely, factors like terrain, vegetation, and building conditions are environment-dependent and are influenced by local climate and weather patterns. Generally, data related to land cover, topographic maps, and three-dimensional mapping contribute to extracting parameters from databases. Characteristics derived from weather conditions, such as temperature, precipitation rate, and humidity, further augment the overall dataset.

Majority of research so far have focused on hand-engineering characteristics in order to construct path loss models; yet, there are issues with this approach's generalizability. The application of the empirical propagation models is limited because they primarily rely on measurement data from particular contexts of interest. In order to overcome this restriction, ray-tracing-based techniques are typically used; unfortunately, they are computationally costly. The models' inability to be broadly applicable is further hampered by the lack of manual feature extraction tools that could be used to describe the intricate geometric and physical characteristics of the propagation environment. Several unneeded and superfluous parameters have been used in earlier research. Filter, wrapper, and embedded feature selection techniques must be used in future research to choose pertinent parameters for the development of a model for predicting path loss with the capability to extrapolate across diverse scenarios. Therefore, a thorough comparison between models based on manually engineered features and models based on automatically extracted features utilizing architectures like convolutional neural networks is required.

C. Algorithms and Hyperparameter Settings

Choosing the right algorithms is crucial to creating a path loss prediction system that is both accurate and efficient. Furthermore, it will be crucial to fine-tune these algorithms' hyperparameters in subsequent studies. There isn't enough research in the literature currently available to thoroughly examine how well the most popular algorithms work for creating path loss prediction models. To choose the best algorithm for the PL prediction system, consideration can be given to various aspects, including the method's complexity and accuracy. The algorithms' hyperparameter values are established prior to the start of the learning process. There are several methods for choosing the ideal hyperparameter settings, including grid and random searches, and bayesian optimization. The settings for the hyperparameters are quite important. Even so, in order to create path loss models, researchers have looked into a variety of neural network topologies, system settings, and learning techniques. Deep learning models form the basis of these in large part. Hence, a comprehensive comparative study is essential to gain deeper insights into incorporating alternative methodologies within computational intelligence.

D. Performance Metrics for Model Evaluation

Previous research has used various performance measures to assess how well their path loss prediction models work. Various metrics, such as mean squared error, root mean square error, correlation factor, maximum prediction error, mean absolute error, mean absolute percentage error, standard deviation error, regression coefficient, prediction time, and accuracy, serve as performance measures in evaluating path loss predictive models. Despite the wide array of metrics available, the lack of a universally accepted standard arises from the diverse performance measurements employed in different studies. It is challenging to fairly compare the performance of previous research that have been published in the literature as each study presents one or more of these metrics. This difficulty should be addressed in future research by offering a thorough assessment of previous experiments utilizing performance measurement clusters. This will shed additional light on the metrics or sets of metrics that should be consistently employed when evaluating path loss prediction systems.

6. Conclusion

This thorough review paper has extensively investigated the present status of path loss prediction using methodologies derived from machine learning and deep learning techniques. It delves into the foundational principles of path loss and its influence on wireless communication systems, addressing the drawbacks of traditional empirical and deterministic models. The paper emphasizes the strengths of machine learning approaches in capturing the intricate and dynamic characteristics of wireless propagation environments. Moreover, the research review delineates the trends in publications and provides a consolidation and examination of studies released on the prognosis of path loss employing models from machine learning and deep learning. Notably, the survey identifies a growing interest in deep learning architectures within the research community, showcasing superior performance compared to traditional machine learning techniques like the Artificial Neural Network. Research employing deep learning for the prediction of path loss heavily depends on the inherent mechanisms for automated extraction of features present in deep learning architectures, in contrast to an exhaustive process of selecting features. The surveyed studies predominantly focus on urban, suburban, rural, or various environments. Challenges in path loss prediction using machine learning approaches are deliberated, and the paper concludes by suggesting future research directions to guide the resolution of these challenges.

References

[1] N. Faruk, N. T. Surajudeen-Bakinde, A. Abdulkarim, S. I. Popoola, A. Abdulkarim, L. A. Olawoyin and A. A. Atayero, "ANFIS Model for Path Loss Prediction in the GSM and WCDMA Bands in Urban Area.," *Journal of Electrical Engineering,* vol. 18, no. 1, p. 1–10, 2019.

[2] N. Faruk, A. O. Adesina and A. A. Ojekunle, "ANN-based model for multiband path loss prediction in built-up environments," *Sci. African,* vol. 17, p. e01350, 2022.

[3] M. K. Elmezughi, O. Salih, T. J. Afullo and K. J. Duffy, "Comparative Analysis of Major Machine-Learning-Based Path Loss Models for Enclosed Indoor Channels," *Sensors,* vol. 22, no. 13, p. 1–25, 2022.

[4] P. Caleb, S. Douglas and G. Dirk, "A Survey of Wireless Path Loss Prediction and Coverage Mapping Methods," *IEEE Communications Surveys & Tutorials,* vol. 15, no. 1, pp. 255-270, 2013.

[5] Friis, "A note on a simple transmission formula," *Proc. IRE,* vol. 34, p. 254–256, 1946.

[6] T. Cogalan, S. Videv and H. Haas, "Operating an In-Cabin Femto-Cellular System Within a Given LTE Cellular Network.," *IEEE Trans. Veh. Technol.,* vol. 67, pp. 7677-7689, 2018.

[7] S. Ojo, A. Sari and T. Ojo, "Path Loss Modeling: A Machine Learning Based Approach Using Support Vector Regression and Radial Basis Function Models," *Open Journal of Applied Sciences,* vol. 12, pp. 990-1010, 2022.

[8] E. Östlin, H.-.. Zepernick and H. Suzuki, "Macrocell path-loss prediction using artificial neural networks," *IEEE Trans. Veh. Technol.,* vol. 59, no. 6, pp. 2735-2747, 2019.

[9] Y. Zhang, J. Wen, G. Yang, Z. He and J. Wang, "Path loss prediction based on machine learning: Principle, method, and data expansion," *Appl. Sci.,* vol. 9, p. 9, 2019.

[10] T. Rappaport, "Wireless Communications: Principles and Practice, 2nd ed.," in *Prentice-Hall: Upper Saddle River*, NJ, USA, 2002.

[11] A. Faris, Marios and C. Angelides, "A machine learning approach to evolving an optimal propagation model for last mile connectivity using low altitude platforms," 2019.

[12] S. Alsamhi, M. Ansari, O. Ma, F. Almalki and S. Gupta, pp. 1-8, 2018.

[13] N. Goncalves and L. Correia, "A propagation model for urban microcellular systems at the uhf band.," *IEEE Trans. Veh. Technol.,* vol. 4, p. 1294 –1302, 2000.

[14] Steendam and M. Moeneclaey, "Analysis and optimization of the performance of ofdm on frequency-selective time-selective fading channels," *IEEE Trans. Commun.,* vol. 47, no. 12, p. 1811 –1819, 1999.

[15] L. Breiman, "Machine Learning," vol. 40, p. 4324, 2001.

[16] L. Breiman, "Random forests," *Mach. Learn,* vol. 45, p. 5–32, 2001.

[17] Isabona, A. Imoize and Y. Kim, "Machine Learning-Based Boosted Regression Ensemble Combined with Hyperparameter Tuning for Optimal Adaptive Learning," *Sensors,* vol. 22, p. 3776, 2022.

[18] T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in *22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 2016.

[19] H. Friedman, "Greedy function approximation: A gradient boosting machine," *Annals of Statistics,* vol. 29, no. 5, pp. 1189-1232, 2001.

[20] M. Uccellari, F. Facchini, M. Sola, E. Sirignano, G. Vitetta, A. Barbieri and S. Tondelli, "On the use of support vector machines for the prediction of propagation losses in smart metering systems," in *IEEE 26th International Workshop on Machine Learning for Signal Processing (MLSP)*, Vietri sul Mare, Italy, 2016.

[21] C. Chang and C. Lin, LIBSVM-A Library for Support Vector Machines, 2003.

[22] Hung, K. Lin, G. Yang and Y. Tsai, "Hybrid support vector regression and GA/TS for radio-wave path-loss prediction," in *International Conference on Computational Collective Intelligence: Technologies and Applicat Springer*, Berlin, Germany, 2010.

[23] Fukushima, S. Miyake and T. Ito, "Neocognitron: a neural network model for a mechanism of visual pattern recognition," *IEEE Trans. Syst. Man Cybern.*, vol. 5, pp. 826-834, 1983.

[24] Y. LeCun, L. Bottou, Y. Bengio and P. Haffner, "Gradient-based learning applied to document recognition," *Proc. IEEE* , vol. 86, no. 11, pp. 2278-2324, 1998.

[25] Ghosh, A. Sufian, F. Sultana, A. Chakrabarti and D. De, "Fundamental Concepts of Convolutional Neural Network," in *Fundamental Concepts of Convolutional Neural Network*, 2020.

[26] Hertel, E. Barth, T. Käster and T. Martinetz, "Deep convolutional neural networks as generic feature extractors," in *In Proceeding of the 2015 International Joint Conference on Neural Networks*, Killarney, Ireland, 2015.

[27] V. Phung and E. Rhee, "A Deep Learning Approach for Classification of Cloud Image Patches on Small Datasets.," *J. Inf. Commun. Converg. Eng.*, vol. 16, p. 173–178, 2018.

[28] C. Haruna, N. Ponman, F. Nasir, A. Emmanuel, Y. O. Imam-Fulani, S. A. Kayode, A. Abubakar, A. O. Abdulkarim, A. S. Olugbenga, G. Salisu, D. U. Aliyu, S. T. Lawan and A. A. Yinusa, "Machine learning modeling for path loss in wireless communication systems: A survey," *Scientific African*, vol. 19, 2023.

[29] J. Wen, Y. Zhang, G. Yang, Z. He and W. Zhang, "Path Loss Prediction Based on Machine Learning Methods for Aircraft Cabin Environments," *IEEE Access*, vol. 7, p. 159251–159261, 2019.

[30] Ahmadien, H. Ates, T. Baykas and B. Gunturk, "Predicting path loss distribution of an area from satellite images using deep learning," *IEEE Access*, p. 64982–64991, 2020.

[31] Wang and H. Lee, "Indoor path loss modeling for 5G Communications in smart factory scenarios based on meta-learning," *Proceedings of the Paper Presented at the 2021 Twelfth International Conference on Ubiquitous and Future Networks (ICUFN)*, 2021.

[32] H. Cheng, S. Ma and H. Lee, "CNN-based mmWave path loss modeling for fixed wireless access in suburban scenarios," *IEEE Antennas Wirel. Propag. Lett*, vol. 19, no. 10, p. 1694–1698, 2020.

[33] R. Levie, Ç. Yapar, G. Kutyniok and G. Caire, "Pathloss prediction using deep learning with applications to cellular optimization and efficient D2D link scheduling," *Proceedings of the Paper Presented at the ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2020.

[34] K. Nobuaki, W. YAMADA, M. SASAKI and Y. TAKATORI, "Convolutional neural network for prediction method of path loss characteristics considering diffrac tion and reflection in an open-square environment," *Proceedings of the Paper Presented at the 2019 URSI Asia-Pacific Radio Science Conference (AP-RASC)*, 2019..

[35] S. Ma, H. Cheng and H. Lee, "A practical approach for indoor path loss modeling based on deep learning," *Comput. Sci. Eng.* , vol. 15, no. 2, p. 84–95, 2021.

[36] N. Kuno, M. Inomata, M. Sasaki and W. Yamada, "Deep learning-based path loss prediction using side-view images in an UMa environment," *Proceedings of the 2022 16th European Conference on Antennas and Propagation (EuCAP), IEEE*, p. 1–5, 2022.

[37] K. Qiu, S. Bakirtzis, H. Song, J. Zhang and I. Wassell, "Pseudo ray-tracing: deep leaning assisted outdoor mm-wave path loss prediction," *IEEE Wirel. Commun. Lett.* , 2022.

[38] S. Sotiroudis, S. Goudos and K. Siakavara, "Deep learning for radio propagation: using image-driven regression to estimate path loss in urban areas," *ICT Express* , vol. 6, no. 3, p. 160–165, 2020.

[39] M. Bal, A. Marey, H. Ates, T. Baykas and B. Gunturk, "Regression of large-scale path loss parameters using deep neural networks," *IEEE Antennas Wirel. Propag. Lett.* , vol. 21, no. 8, p. 1562–1566, 2022.

[40] J. Thrane, D. Zibar and H. Christiansen, "Model-aided deep learning method for path loss prediction in mobile communication systems at 2.6GHz," *IEEE Access* , vol. 8, p. 7925–7936, 2020.

[41] S. Sotiroudis, P. Sarigiannidis, S. Goudos and K. Siakavara, "Fusing diverse input modalities for path loss prediction: a deep learning approach," *IEEE Access* , vol. 9, p. 30441–30451, 2021.

[42] J. Lee, M. Kang and S. Kim, "Path loss exponent prediction for outdoor millimeter wave channels through deep learning," in *Proceedings of the Paper Presented at the 2019 IEEE Wireless Communications and Networking Conference (WCNC)*, 2019.

[43] S. Sotiroudis, S. Goudos and C. Christodoulou, "A hybrid CNN-NGBoost model for probabilistic image-driven path loss prediction," in *Proceedings of the 2022 IEEE International Symposium on Antennas and Propagation and USNC-URSI Radio Science Meeting (AP-S/URSI), IEEE*, 2022.

[44] H. Ates, S. Hashir, T. Baykas and B. Gunturk, "Path loss exponent and shadowing factor prediction from satellite images using deep learning," *IEEE Access* , vol. 7, p. 101366–101375, 2019.

[45] R. Juang, "Deep learning-based path loss model in urban environments using image-to-image translation," *IEEE Trans. Antennas Propag.* , 2022.

[46] U. Sani, D. Lai and O. Malik, "A hybrid combination of a convolutional neural network with a regression model for path loss prediction using tiles of 2D satellite images," in *Proceedings of the Paper Presented at the 2020 8th International Conference on Intelligent and Advanced Systems (ICIAS)*, 2021.

[47] H. Cheng, S. Ma, H. Lee and M. Cho, "Millimeter wave path loss modeling for 5G communications using deep learning with dilated convolution and attention," *IEEE Access* , vol. 9, p. 62867–62879, 2021.

[48] Z. Adeyemo, T. Olawuyi, O. Oseni and S. Ojo, "Development of a path-loss prediction model using adaptive neuro-fuzzy inference system," *Int. J. Wirel. Microw. Technol.* , vol. 9, no. 6, p. 40–53, 2019.

[49] W. Bhupuak and S. Tooprakai, "Minimizing path loss prediction error using k-means clustering and fuzzy logic," *Turk. J. Electr. Eng. Comput. Sci.* , vol. 26, no. 4, p. 1989–2002, 2018.

[50] H. Cruz, R. Nascimento, J. Araujo, E. Pelaes and G. Cavalcante, "Methodologies for path loss prediction in LTE-1.8GHz networks using neuro-fuzzy and ANN," in *Proceedings of the Paper Presented at the 2017 SBMO/IEEE MTT-S International Microwave and Optoelectronics Conference (IMOC)*, 2017.

[51] T. Dalkiliç, B. Hanci and A. Apaydin, "Fuzzy adaptive neural network approach to path loss prediction in urban areas at GSM-900 band," *Turk. J. Electr. Eng. Comput. Sci.* , vol. 18, no. 6, p. 1077–1094, 2010.

[52] Danladi and P. Vasira, "Path loss modeling for next generation wireless network using fuzzy logic-spline interpolation technique," *J. Eng. Res. Rep.* , p. 1–10, 2018.

[53] Gupta, K. Ghanshala and R. Joshi, "Path loss predictions for fringe areas using adaptive neuro-fuzzy inference system," *Int. J. Syst. Assur. Eng. Manag.* , p. 1–14, 2021.

[54] V. Gupta and S. Sharma, "Secure path loss prediction in fringe areas using fuzzy logic approach," in *Proceedings of the Paper Presented at the 2009 International Conference on Advances in Computing, Control, and Telecommunication Technologies*, 2009.

[55] M. Jafri, J. Ely and L. Vahala, "Interference path loss prediction in A319/320 Airplanes using modulated fuzzy logic and neural networks," in *Proceedings of the Paper Presented at the NAFIPS 2007-2007 Annual Meeting of the North American Fuzzy Information Processing Society*, 2007.

[56] S. Mathew, K. Shylaja, T. Jayasri and M. Hemalatha, "Path loss prediction in wireless communication system using fuzzy logic," *Indian J. Sci. Technol*, vol. 7, no. 5, p. 642–647, 2014.

[57] S. Phaiboon, P. Phokharutkul and S. Somkurnpanich, "Mobile propagation path loss models for suburban areas using fuzzy logic approximation," in *Proceedings of the Paper Presented at the 2004 IEEE Region 10 Conference TENCON 2004*, 2004.

[58] S. Phaiboon, P. Phokharatkul and S. Somkuarnpanit, "2 to 16GHz microwave line-of-sight path loss prediction on urban streets by fuzzy logic models," in *Proceedings of the Paper Presented at the TENCON 2005-2005 IEEE Region 10 Conference* , 2005.

[59] S. Phaiboon, P. Phokharatkul and S. Somkuarnpanit, "Muti-layer fuzzy logic sets for mobile path loss in forests," in *Proceedings of the Paper Presented at the TENCON 2006-2006 IEEE Region 10 Conference*, 2006.

[60] S. Phaiboon and P. Phokharatkul, "An empirical based path loss model with tree density effects for 1.8GHz mobile communications using fuzzy regression,," *WSEAS Trans. Commun.* , vol. 5, no. 3, p. 564–571, 2006.

[61] M. Salman, S. Popoola, N. Faruk, N. Surajudeen-Bakinde, A. Oloyede and L. Olawoyin, "Adaptive Neuro-Fuzzy model for path loss prediction in the VHF band," in *Proceedings of the Paper Presented at the 2017 International Conference on Computing Networking and Informatics (ICCNI)*, 2017.

[62] Shoewu, M. Adedoyin, L. Akinyemi and L. Oborkhale, "Fuzzy-logic based path loss models for Metropolitan environment," in *Proceedings of the Paper Presented at the 2018 IEEE International Workshop on Signal Processing Systems (SiPS)*, 2018.

[63] N. Surajudeen-Bakinde, N. Faruk, S. Popoola, M. Salman, A. Oloyede, L. Olawoyin and C. Calafate, "Path loss predictions for multi-transmitter radio propagation in VHF bands using Adaptive Neuro-Fuzzy Inference System," *Eng. Sci. Technol. Int. J.* , vol. 21, no. 4, p. 679–691, 2018.

[64] L. Wu, D. He, B. Ai, J. Wang, H. Qi, K. Guan and Z. Zhong, "Artificial neural network based path loss prediction for wireless communication network," *IEEE Access* , vol. 8, p. 199523–199538, 2020.

[65] Y. Wang, M. Liang, J. Hu and T. Song, "A new method for radio wave propagation prediction based on BP-neural network and path loss model," in *Proceedings of the Paper Presented at the 2020 12th International Conference on Knowledge and Smart Technology (KST)*, 2020.

[66] S. Ojo, A. Imoize and D. Alienyi, "Radial Basis Function Neural Network path loss prediction model for LTE networks in multitransmitter signal propagation environments," *Int. J. Commun. Syst.*, vol. 34, no. 3, 2021.

[67] H.-S. Jo, C. Park, E. Lee, H. K. Choi and J. Park, "Path loss prediction based on machine learning techniques: Principal component analysis, artificial neural network, and Gaussian process," *Sensors*, vol. 20, no. 7, p. 1927, 2020.

[68] O. J. Eichie Oyedum, D. O. Ajewole and M. A. Aibinu, "Comparative Analysis of Basic Models and Artificial Neural Network Based Model for Path Loss Prediction," *Prog. Electromagn. Res.*, vol. 61, p. 133–146, 2017.

[69] Park, D. Tettey and H.-S. Jo, "Artificial Neural Network Modeling for Path Loss Prediction in Urban Environments," 2019.

[70] Popescu, D. Nikitopoulos, P. Constantinou and I. Nafornita, "Comparison of ANN based models for path loss prediction in indoor environment," in *Proceedings of the Paper Presented at the IEEE Vehicular Technology Conference*, 2006.

[71] S. P. Sotiroudis, S. K. Goudos and K. Siakavara, "Neural networks and random forests: A comparison regarding prediction of propagation path loss for NB-IoT networks," *In 2019 8th International Conference on Modern Circuits and Systems Technologies (MOCAST),* pp. 1-4, 2019.

[72] S. Popoola, N. Faruk, A. Oloyede, A. Atayero, N. Surajudeen-Bakinde and L. Olawoyin, "Characterization of path loss in the VHF band using neural network modeling technique," in *Proceedings of the Paper Presented at the 2019 19th International Conference on Computational Science and Its Applications (ICCSA)*, 2019.

[73] N. Zaarour, S. Affes, N. Kandil and N. Hakem, "Comparative study on a 60GHz path loss channel modeling in a mine environment using neural networks," in *Proceedings of the Paper Presented at the 2015 IEEE International Conference on Ubiquitous Wireless Broadband (ICUWB)*, 2015.

[74] Y. Egi and C. E. Otero, "Machine-learning and 3D point-cloud based signal power path loss model for the deployment of wireless communication systems.," *IEEE Access,* vol. 7, pp. 42507-42517, 2019.

[75] M. Piacentini and F. Rinaldi, "Path loss prediction in urban environment using learning machines and dimensionality reduction techniques.," *Comput. Manag. Sci.,* vol. 8, no. 4, p. 371–385, 2011.

[76] N. Moraitis, L. Tsipis, D. Vouyioukas, A. Gkioni and S. Louvros, "Performance evaluation of machine learning methods for path loss prediction in rural environment at 3.7 GHz," *Wireless Networks*, vol. 27, no. 6, p. 4169–4188, 2021.

[77] H. Singh, S. Gupta, C. Dhawan and A. Mishra, "Path loss prediction in smart campus environment: machine learning-based approaches," in *Proceedings of the Paper Presented at the 2020 IEEE 91st Vehicular Technology Conference (VTC2020-Spring)*, 2020.

[78] Fu, P. Juyal, E. Jorgensen and A. Zajic, "Comparison of Statistical and Deep Learning Path Loss Model for Motherboard Desktop Environment," in *Proceedings of the 2022 16th European Conference on Antennas and Propagation (EuCAP), IEEE*, 2022.

[79] Tahat, T. Edwan, H. Al-Sawwaf, J. Al-Baw and M. Amayreh, "Simplistic machine learning-based air-to-ground path loss modeling in an urban environment," in *Proceedings of the Paper Presented at the 2020 Fifth International Conference on Fog and Mobile Edge Computing (FMEC)*, 2020.

[80] S. Duangsuwan, P. Juengkittikul and M. Myint, "Path loss characterization using machine learning models for GS-to-UAV-enabled communication in smart farming scenarios," *Int. J. Antennas Propag*, 2021.

[81] M. Kalakh, N. Kandil and N. Hakem, "Neural networks model of an UWB channel path loss in a mine environment," in *Proceedings of the Paper Presented at the 2012 IEEE 75th Vehicular Technology Conference (VTC Spring)*, 2012.

[82] M. Ayadi, A. Zineb and S. Tabbane, "A UHF path loss model using learning machine for heterogeneous networks," *IEEE Trans. Antennas Propag.* , vol. 65, no. 7, p. 3675–3683, 2017.

[83] F. e. a. N, ANFIS Model for Path Loss Prediction in the GSM and WCDMA Bands in Urban Area, vol. 18, Elektr. J. Electr. Eng., 2019, p. 1–10.

[84] M. K. Elmezughi, O. Salih, T. J. Afullo and K. J. Duffy, "Comparative Analysis of Major Machine-Learning-Based Path Loss Models for Enclosed Indoor Channels," *Sensors,* vol. 22, p. 1–25, 2022.

[85] T. S. Rappaport and e. al., "Wireless Communications: Principles and Practice.," *Pearson,* 2017.

[86] J. Goldsmith, "Wireless Communications.," *Cambridge University Press,* 2005.

[87] A. M. Saleh and R. A. Valenzuela, "A Statistical Model for Indoor Multipath Propagation," *IEEE Journal on Selected Areas in Communications,* vol. 5, no. 2, pp. 128-137, 1987.

[88] G. Proakis, "Digital Communications.," *McGraw-Hill Education,* 2001.

[89] G. Yang, Y. Zhang, Z. He, J. Wen, Z. Ji and Y. Li, "Machine-learning-based prediction methods for path loss and delay spread in air-to-ground millimetre-wave channels," *IET Microwaves, Antennas & Propagation,* vol. 13, no. 8, pp. 1113-1121, 2019.

[90] O. R. Omasheye, S. Azi, J. Isabona, A. L. Imoize, C.-T. Li and C.-C. Lee, "Joint random forest and particle swarm optimization for predictive pathloss modeling of wireless signals from cellular networks.," *Future Internet,* vol. 14, no. 12, p. 373, 2022.

[91] S. Ojo, M. Akkaya and J. C. Sopuru, "An ensemble machine learning approach for enhanced path loss predictions for 4G LTE wireless networks.," *International Journal of Communication Systems,* p. 35, 2022.

[92] Alfaresi, Z. Nawawi, B. Y. Suprapto, C.-T. Li and C.-C. Lee, "Development of path loss prediction model using feature selection-machine learning approach: Improvement of path loss prediction accuracy in mixed land-water case," *International Journal of Advanced Computer Science and Applications,* vol. 13, no. 10, pp. 349-356, 2022.

[93] S. Aldossari and K. C. Chen, "Predicting the path loss of wireless channel models using machine learning techniques in mmWave urban communications," *arXiv preprint arXiv,* 2020.

[94] Zreikat and M. Dordevic, "Performance analysis of path loss prediction models in wireless mobile networks in different propagation environments.," *In Proceedings of the 3rd World Congress on Electrical Engineering and Computer Systems and Science (EECSS'17),* pp. 1-11, 2017.

[95] S. I. Popoola Adetiba, E. Atayero, A. A. Mathews, V. O. Faruk and N. C. T. Calafate, "Optimal Path Loss Prediction Model For Rural Propagation Environments Using Feed-Forward Neural Networks," *Cogent Eng. , Taylor Fr.,* p. 144–434, 2018.

[96] Popescu Nafornita and P. Constantinou, "Comparison of Neural Network Models for Path Loss Prediction," *IEEE Int. Conf. Wirel. Mob. Comput. Netw. Commun.,* p. 44–49, 2005.

[97] C. Delos Angeles and E. P. Dadios, "Heuristic Modelling of Path Loss Inside Residences at 677 MHz.," *8th IEEE Interational Conf. Humanoid, Nanotechnology, Inf. Technol. Cebu IEEE,* 2015.

[98] N. Zaarour Kandil, N. Hakem and C. Despins, "Comparative experimental study on modeling the path loss of an UWB channel in a mine environment using MLP and RBF neural networks.," *Int. Conf. Wirel. Commun. Undergr. Confin. Areas,* 2012.

[99] O. J. Famoriji and T. Shongwe, "Path loss prediction in tropical regions using machine learning techniques: A case study," *Electronics,* vol. 11, no. 9, p. 2711, 2022.

[100] Wu, D. He, B. Ai, J. Wang, H. Qi, K. Guan and Z. Zhong, "Artificial neural network based path loss prediction for wireless communication network," *IEEE Access,* vol. 8, pp. 199523-199545, 2020.

[101] S. I. Popoola, A. Jefia, A. A. Atayero, O. Kingsley, N. Faruk, O. F. Oseni and R. O. Abolade, "Determination of neural network parameters for path loss prediction in very high frequency wireless channel," *IEEE Access,* vol. 7, pp. 150462-150484, 2019.

[102] J. Wen, Y. Zhang, G. Yang, Z. He and W. Zhang, "Path loss prediction based on machine learning methods for aircraft cabin environments," *IEEE Access,* vol. 7, pp. 159251-159261, 2019.

[103] K. Elmezughi, O. Salih, T. J. Afullo and K. J. Duffy, "Comparative analysis of major machine-learning-based path loss models for enclosed indoor channels," *Sensors,* vol. 22, no. 13, p. 4967, 2022.

[104] Y. Zhang, J. Wen, G. Yang, Z. He and X. Luo, "Air-to-air path loss prediction based on machine learning methods in urban environments," *Wireless Communications and Mobile Computing,* p. 8489326, 2018.

[105] G. Vergos, "Comparing different machine learning algorithms for the prediction of path loss in wireless communications (Bachelor's dissertation, Aristotle University of Thessaloniki)," *Retrieved from arXiv,* 2021.

[106] Navarro, D. Parada, D. Guevara, C. G. Rego and R. A. Badillo, "Modified Two-Ray Model with UTD and Atmospheric Effects," *In 2020 14th European Conference on Antennas and Propagation (EuCAP),* pp. 1-5, 2020.

[107] H. Gonsioroski, L. R. Leão Junior, A. B. C. dos Santos and L. d. S. Mello, "Optimization of path loss prediction in urban and suburban environments in 2.3-2.4 GHz using OLS nonlinear regression and artificial neural networks," *In Proceedings of International Conference on Modeling, Analysis and Simulation of Wireless and Mobile Systems (MSWIM'22),* 2022.

[108] Moraitis, L. Tsipi and D. Vouyioukas, "Machine learning-based methods for path loss prediction in urban environment for LTE networks.," *In 2020 16th international conference on wireless and mobile computing, networking and communications (WiMob),* pp. 1-6, 2020.