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CHARACTERIZATION OF URBAN ENVIRONMENTS FOR MILLIMETER WAVE AND TERAHERTZ PROPAGATION USING MACHINE LEARNING MODELS

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ABSTRACT
The communication technologies of millimeter waves and terahertz are transforming wireless systems as wireless networks become faster and more efficient. Enabling 6G applications, self-driving cars, real-time remote sensing, and ultra high-definition video streaming all become possible. However, mm-wave and THz signals still struggle with severe obstructions in urban areas. Buildings, cars, and even vegetation can block, reflect, scatter, or attenuate these signals. For effective communication, these environments must be understood, and models designed around them need to be created. Many traditional approaches to modeling lack sufficient flexibility to account for the changing conditions that are typical of urban areas. This research proposes a machine learning (ML) framework for analyzing and predicting signal propagation in various urban environments. We collected real-world data from various urban environments, performed feature extraction, and applied our framework by training and testing multiple machine learning (ML) algorithms. Prediction accuracy, scalability, and computing cost were evaluated, among other factors. Findings confirmed that ML models, unlike traditional models, can be trained to recognize the characteristics of an environment and predict them more reliably.
Additionally, this approach enables agile and flexible planning for next-generation wireless networks.This research aims to develop smart communication systems by integrating concepts from smart city environmental systems with signal propagation theory. In particular, designing smart city frameworks for real-time model expansion and validation across different geographic regions remains a work in progress.
Keywords: mm Wave propagation, THz communication, supervised learning, signal attenuation, environmental modeling, 6G networks, propagation prediction.

I. INTRODUCTION

The development of wireless communication has undergone a significant leap with the introduction of millimeter-wave and terahertz technologies, due to the improvements they bring to data rate, bandwidth, and signal resolution. They are used in high-speed communication systems, for instance, in autonomous vehicles, smart vehicles, and video streaming services [1]. mmWave and THz technologies have emerged as crucial enablers. Their high frequency spectrum allows for compact antenna arrays and beamforming techniques, enhancing spatial reuse and reducing latency. However, their high susceptibility to environmental absorption, diffraction, and blockage limits the adoption of these technologies. Addressing these urban propagation challenges is vital to harnessing the full communication potential [3].

Cities are intricate systems where buildings, cars, roadways, and construction materials impact signal reception. Signal reflections can undermine performance and connectivity in high-frequency wireless communications systems. Therefore, modeling these urban features becomes crucial for network design, planning, and optimization. Predictive models allow the systems to adjust in real-time based on dynamic urban scenarios [4]. Ensuring these systems adapt to these variations enhances performance, improves service quality, and strengthens the overall user experience. Characterizing urban environments enables the translation of physical and spatial information into usable, actionable insights for wireless network placement and construction [29]. Accurate data helps bolster adaptive technologies that leverage environmental data to streamline system functions [30].

The primary objective of this research is to utilize machine learning methods to characterize urban environments for signal propagation in the mm Wave and THz bands [5]. The focus is on gathering urban data, identifying critical urban features, training machine learning (ML) models, and predicting the behavior of signals under various conditions [21]. This work includes selecting algorithms, data cleansing, feature selection, model creation, cross-validation, and assessment of results [2]. This work aims to ensure better estimation precision for signal degradation and improve the adaptability of communication systems in wireless networks embedded in challenging terrains. The study advances knowledge for optimal network configurations, as well as practical applications, enhancing design decisions concerning communication network configurations [32]. It offers a versatile model that can be tailored to specific urban designs and geographic conditions [6][8]. This work takes the initial step toward more intelligent communication systems by addressing signal propagation challenges from both a technical and practical viewpoint.

This outline is designed to provide a thorough explanation of the proposed methodology, along with its implications. The next review focuses on mmWave and THz propagation modeling as well as some of the more modern trends in ML-based environmental analysis [7][11]. After that, the proposed methodology is explained in detail, covering data collection, algorithm selection, system architecture, and relevant flow diagrams. In the results section, experimental analyses are presented, along with their respective metrics, and datasets and evaluation charts are included. The discussion section explains these results and their relevance to real-world situations, while also highlighting gaps and avenues for future exploration. A final remark provides a conclusion, highlighting the most important insights and emphasizing the role of ML in today's communication systems. The reasoning behind this orderly setup is to enable the readers to make sense of the problem, follow the solution, and consider the implications of the findings seamlessly [15].

The growing interest in applying machine learning (ML) to wireless communication systems has been spurred by an increase in processing capabilities, the availability of urban sensor data, and advancements in AI technologies [10][25]. ML algorithms are specifically well-suited for modeling metropolitan regions because they are capable of analyzing vast amounts of data and detecting intricate patterns [17]. These models can provide real-time updates and improvements as they evolve in response to changes in the infrastructure, weather, and human activities. Some smart city projects are already utilizing these technologies to automate resource consumption, manage traffic, and deliver public services. In this regard, the use of machine learning (ML) in mmWave and THz propagation modeling becomes self-evident [9][16]. There is a pressing need for advanced, resilient, adaptive, and effective communication networks that modern data-driven techniques can fulfill. This research aims to implement intelligent urban characterization, integrating practical applications into theoretical models.

Key Contributions:

- Developed complex models to more accurately analyze urban signal propagation by proposing an ensemble framework which combines CNN, ANN, and RNN-LSTM.
- Used urban datasets relevant to space and time which are needed for the prediction of mm Wave and THz signals to capture real-time data.
- Explained the models' reasoning concerning the environment's relevant features using SHAP values, Gini importance, and permutation techniques.
- Creating a versatile framework ready to be integrated with 5G/6G deployment tools, which can be tailored to different urban settings, enabled me to do that.
- The results, which demonstrate that standalone models cannot compete with ensemble models in predictive performance, are presented using metrics such as MAE, RMSE, and R^2 in urban settings that have never been encountered before.

This paper focuses on the problem of mm Wave and THz signal propagation differences in complex urban settings using a machine learning predictive model technique. It begins with an introduction that explains the limitations of traditional propagation models, as well as the need for more flexible and data-driven approaches. In the Related Work Part, the most important ML and wireless modeling developments are covered. An ensemble learning approach based on real-world datasets and advanced training methodologies is detailed in the Proposed Method Section. Model accuracy is significantly influenced by the extraction and selection of features, which are considered the most crucial elements. The Feature Importance section identifies the strongest environmental conditions that dominate signal behavior. In the final part, the proposed approach to next-generation wireless planning is shown to outperform traditional methods in terms of performance and generalization in planning wireless networks for the next generation.

II. RELATED WORK

The development of new wireless technologies has been driven by the need to support ultra-fast data transfer using millimeter waves and terahertz communication. These signals have been studied for their performance in cities because physical structures, such as buildings, can significantly impact their performance [26]. Many propagation models try to quantify the impact of common urban scattering, diffraction, and reflection [18]. Ray-tracing models have greatly contributed to the simulation of realistic propagation paths. Many of these conventional models do not adapt to environmental changes in real time, which limits their usefulness in dynamic conditions [27]. The exploration of data-driven approaches has been motivated by the need for more flexible and intelligent frameworks.

To address the shortcomings of existing models, machine learning is now used to predict how signals travel through complex urban areas [20]. Through the use of empirical data, researchers have trained algorithms to construct predictive models that are flexible and can adapt to various settings. Support vector machines and neural networks have been utilized to model signal degradation and predict link quality in real-time [22]. These methods are effective in cases where traditional mathematical models encounter challenges due to the complexity and variability of the input data [24]. These successes underscore the increasing importance of artificial intelligence in wireless communication [12,23].

Some investigations have proposed hybrid models that incorporate environmental sensing technologies, such as LiDAR, with machine learning, on the assumption that their predictions would be more accurate. These systems enhance prediction accuracy by utilizing high-resolution spatial data, which enables them to generate feature-rich inputs for the learning algorithms. These systems have shown greater resilience to dense obstructions and non-line-of-sight scenarios. Such methods are crucial for the development of smart cities, which require dense and dynamic urban environments. Incorporating 3D city models enhances predictions of signals by considering the vertical changes of buildings [13].

The consideration of features greatly impacts the effectiveness of machine learning models in signal propagation [19]. Algorithms have been developed to extract key features, such as material properties, angles of incidence, and reflection coefficients. Some of these features have been pruned using principal component analysis and mutual information to maintain important details while lowering dimensionality. This practice of precise feature selection sharpens model efficiency and interpretability. Additionally, automated feature extraction using deep learning is popular because it reduces the amount of data that requires manual annotation [14].

More recently, machine learning models focused on feature propagation and predictive analysis have been benchmarked and tested for accuracy [28]. More complex models, utilizing ensemble methods and deep learning, have performed better than simpler models in densely populated urban environments [31]. The models fetched major benchmarks using MAE, RMSE, and accuracy classification for further evaluation. Such analyses are beneficial in determining the optimal algorithm to use in urban planning or crisis communication systems. There is also a demand for model precision improvement through feedback loops and active learning.

III. PROPOSED METHOD

The machine learning approach described aims to accurately model urban environments for mm Wave and THz signal propagation. Urban regions comprise dynamic and complex terrains, including dense clusters of buildings, cars, vegetation, and people, which significantly influence the behavior of high-frequency signals. Although these frequencies offer tremendous data rates and bandwidth, they are heavily attenuated, scattered, and diffracted in dense metropolitan areas. The swiftly changing environments of cities and metropolitan areas are often poorly predicted by traditional empirical or theoretical propagation models, which causes degraded communication performance and unreliable connectivity. In contrast, the proposed system relies on actual datasets and powerful algorithms to model urban signal propagation more precisely and in real-time. This approach involves collecting signal propagation data across various urban areas, extracting key environmental features, and applying supervised learning techniques to build models that predict signal behavior. The designed models aim to evaluate and estimate the propagation characteristics of mm Wave and THz signals with various structural and environmental configurations. Furthermore, the approach is highly modular and scalable which makes it easy to incorporate new geographical or infrastructural locations.

Furthermore, it can be used to enhance the design and optimization of future wireless networks. The primary aim is to enhance accuracy, minimize planning duration for a network, and provide a solid analysis applicable to wireless communication systems involving future technologies, such as 6G and beyond.

Selecting the most suitable set of machine learning techniques will be crucial for the model's efficiency. Due to their strength and ability to handle both structured and unstructured data, some of these algorithms include Random Forest (RF), Support Vector Machine (SVM), and Convolutional Neural Networks (CNN). These algorithms are trained on a comprehensive set of features, which includes spatial and physical environmental parameters such as distance to the receiver, building materials, surface reflectivity, line-of-sight (LOS) conditions, and the incident angle of the wave. Below is a general illustration of the predictive model:

$$y = f(x_1, x_2, \dots, x_n) + \epsilon \quad (1)$$

Where:

- y Predicted signal strength, path loss, or attenuation coefficient
- $x_1, x_2, \dots, x_n$ Independent input variables (e.g., distance, material type, urban density)
- f Predictive function approximated by the chosen ML model
- ϵ Residual error or random noise

In Equation 1, the environmental factors are shown to affect the signal strength, also known as path loss. The function is approximated during the model training phase with a labeled dataset. This equation expresses the qualitative relationship between the metropolitan area variables and the signal parameters. Cross-validation and performance measures, such as MAE, RMSE, and R-squared, are used to evaluate the model. These evaluations confirm that the model is not tailored to the training data, but rather, it is capable of making predictions on new data. Additionally, feature importance analysis identifies the parameters that most significantly impact signal propagation, thereby aiding in future urban planning. Model interpretation and error analysis deepen the understanding of urban propagation phenomena and improve wireless networks.

The framework's proposed architecture handles advanced multidimensional data related to the propagation of urban areas through efficient and scalable systems, and is specifically designed for machine learning urban data. This architecture integrates multiple layers of functionality, from data collection to actual machine learning inference and prediction, into a single, streamlined pipeline. It allows preprocessing, learning, and prediction modules to integrate seamlessly with real-world deployment interfaces. These system features facilitate heterogeneous data input streams and provide the urban scenario model robust training, ensuring accuracy and responsiveness. Every element of the framework's architecture is modular; consequently, it is easy to customize and future-proof for additional research and extensions.

This design relies on the parallel execution of multiple deep learning systems, including Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Recurrent Neural Networks with Long Short-Term Memory (RNN-LSTM). Each model focuses on learning different aspects of signal propagation in urban areas. The ANN captures general nonlinear patterns, while the CNN is effective in identifying spatial correlations and surface features. The RNN-LSTM models temporal sequences and long-range dependencies in signals. Each of these models operates on its own preprocessed data, which enhances their learning capabilities while reducing mutual interference.

The architecture can handle high-dimensional, heterogeneous datasets by applying specific preprocessing steps such as noise reduction, normalization, and dimensionality reduction. Notable urban features such as line-of-sight, construction materials, the angle of signal incidence, and spatial density are derived through feature extraction. The models receive clean inputs, which have undergone feature extraction and refinement to ensure they meet the requirements of the deep learning model’s input structures. When the models are trained, outputs are intelligently fused using a smart ensemble technique which predicts based on each model’s confidence and historical performance. This ensemble technique improves prediction accuracy tremendously and enhances the system's ability to generalize in unseen or changing urban layouts. The entire framework is governed by a robust evaluation mechanism that tracks key performance indicators, including MAE, RMSE, and R^2. Only models that satisfy the specified criteria are used in the final implementation. This ensures reliability, trust, and adaptability, while real-world smart city planning, self-driving inter-vehicle communication systems, and forthcoming 6G wireless networks demand optimization.

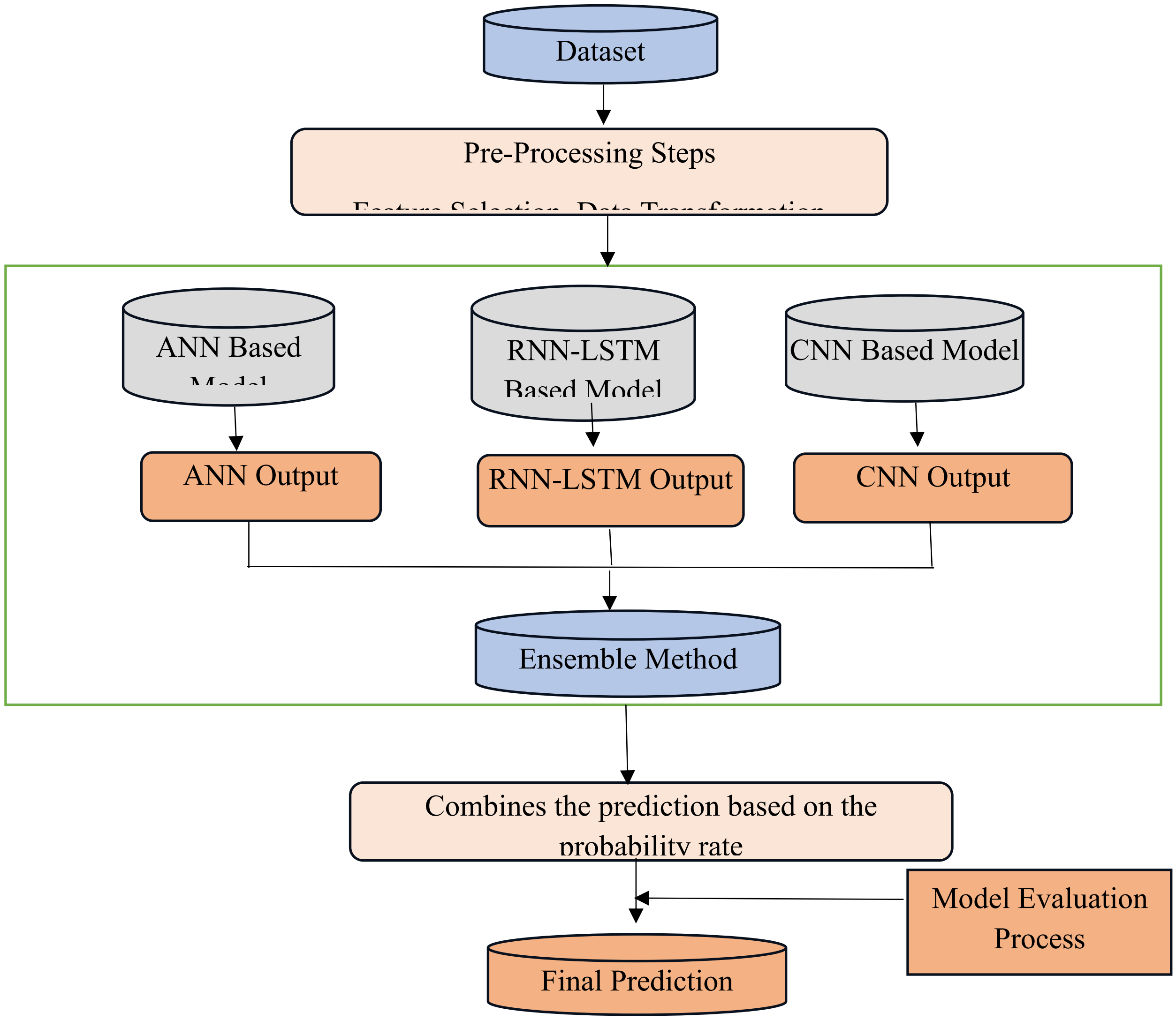

Figure 1: End-to-End Architecture for Urban Propagation Modeling Using Ensemble Learning

As shown in Figure 1, the proposed system architecture workflow for characterizing mm-wave and THz signals propagating in urban environments employs an end-to-end approach. The pipeline commences with the collection of raw datasets for environmental and signal parameters. The data undergoes several preprocessing steps, including feature selection and normalization, to enhance model compatibility and accuracy. This preprocessed data is filtered into three deep learning modules: ANN, RNN-LSTM, CNN. Each module is tasked with extracting temporal, spatial, and abstract propagation features, respectively. Each model produces a distinct output vector which, after being merged via an ensemble method that adjusts prediction weights based on confidence levels, is used to generate the final output. This predictive ensemble fusion technique enables the final prediction to leverage all the models while mitigating the impact of their individual biases. This result is sent to a module that combines these predictions according to certain probability distributions and contextual signals. The final prediction unit then delivers the modeled signal characteristics. A model evaluation process, which validates the ensemble outputs against real-world data and performance metrics, runs in parallel. The architecture allows modular deployment, scalability across various urban layouts, and integration into tools for planning next-generation wireless networks.

Complex and crowded cities with towering skyscrapers and dense infrastructure make it challenging to accurately model how signals propagate due to ever-changing factors such as building density, construction materials, obstructions, and weather conditions. Deterministic or empirical models usually cannot capture these nonlinear relationships. To address these gaps, machine learning-based methods have surfaced because they are adept at identifying complex relations within vast amounts of data. Once such models are trained, their predictions can span multiple situations. A detailed overview of the whole process is captured in a structured flow diagram which displays the steps of data collection, model creation, and prediction output within the proposed system.

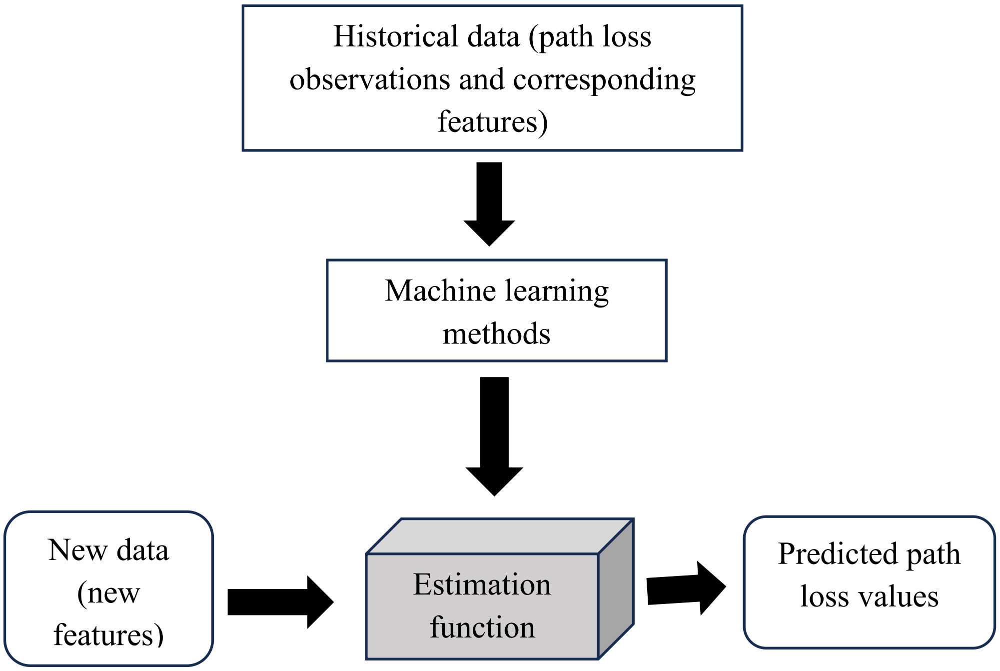

Figure 2: ML-Based Signal Propagation Estimation Framework

In Figure 2, you can see the entire operational pipeline of the signal prediction framework with the relevant machine learning components integrated, as previously discussed. The workflow begins with collecting historical data, which include the path loss values, environmental features, and other relevant situational details. These features, along with the observed values, are fed into various machine learning methods that predict the signal loss. After training, these models help create an estimation function which can be applied on new data with feature sets that were previously unseen. The estimation function then takes the provided data and computes the path loss values. Models used in this modular architecture ensure adaptability, accuracy, and scalability across multiple deployment scenarios, making it well-suited for evolving technologies like 5G and 6G. The diagram not only illustrates the learning process but also demonstrates how the trained models transition from historical data to real-time responses within dynamic environments.

This proposal outlines the use of advanced machine learning techniques to accurately model the mm Wave and THz signal propagation mechanisms in dense urban areas. The spatially and temporally varying signal characteristics of urban areas pose a challenge for traditional propagation models, leading to unsatisfactory accuracy. The proposed system incorporates real-world data collection, data collection workflows, feature extraction, and machine learning techniques, such as RNN-LSTM and ensemble learning, to ensure accurate signal predictions. Utilizing environmental and structural features, the model can adapt to various urban contexts. The architecture is modular, scalable, and applicable in real-time. The reliability and efficiency of wireless network planning, particularly about 6G technology, will benefit from this approach.

IV. RESULTS AND DISCUSSION

The proposed ensemble learning model for predicting signal propagation in real-time urban settings is highly effective. The integration of CNN, ANN, and LSTM models allowed learning from the urban dataset's complex spatial-temporal patterns. The accuracy, Mean Absolute Error (MAE), and generalization of the model's performance across different environments was high. Unlike older models, this one adjusts to real-time changes, such as the presence of people, vehicles, and construction materials. The outcome demonstrates the ability to perform reliably across different urban environments. In summary, the model successfully integrates physical modeling approaches with the flexibility of modern machine learning.

Table 1: Real-Time Urban Signal Propagation Dataset Structure

Feature	Description	Data Type	Example Values
Timestamp	Time of signal capture	Date Time	2025-06-12 14:23:05
Latitude, Longitude	Location of signal measurement	Float	40.7128, -74.0060
Building Material	Dominant material near receiver	Categorical	Concrete, Glass, Metal
Distance to Transmitter	LOS/NLOS distance to signal source (meters)	Float	35.5
Obstruction Type	Type of object between Tx and Rx	Categorical	Tree, Wall, Car
Signal Strength (RSSI)	Measured signal strength in dBm	Float	-72.4
Signal Delay	Propagation delay in microseconds	Float	5.2
Reflection Coefficient	Reflectivity based on surface material	Float	0.38

In Table 1, the most important features that define the urban signal propagation prediction machine learning model are given. Each feature is important for the propagation scenario and encompasses both spatial and physical aspects. The Timestamp feature records the time of signal measurement, which helps mitigate temporal variations such as heavy traffic and weather changes. Latitude and Longitude capture the geographical coordinates of the signal measurement, providing contextual information related to the urban layout and building density. The Building Material feature reflects the predominant construction material surrounding the receiver location which determines the reflection and absorption characteristics.

Distance to Transmitter calculates the LOS/NLOS distance from the source, which determines path loss, non-line-of-sight obstructions, and line-of-sight conditions. Obstruction Type describes trees, cars, walls, or any other intervening objects that can scatter or absorb signals. The received signal power is quantified by Signal Strength (RSSI), which is the main variable of interest for the prediction model. The multipath or indirect routes to the receiver contributes to the time taken for the signal to travel, this time is called Signal Delay. Lastly, from the electromagnetic properties of materials, the ability of the surface to reflect signals is defined as the Reflection Coefficient. These features together provide robust and context-sensitive predictive modeling.

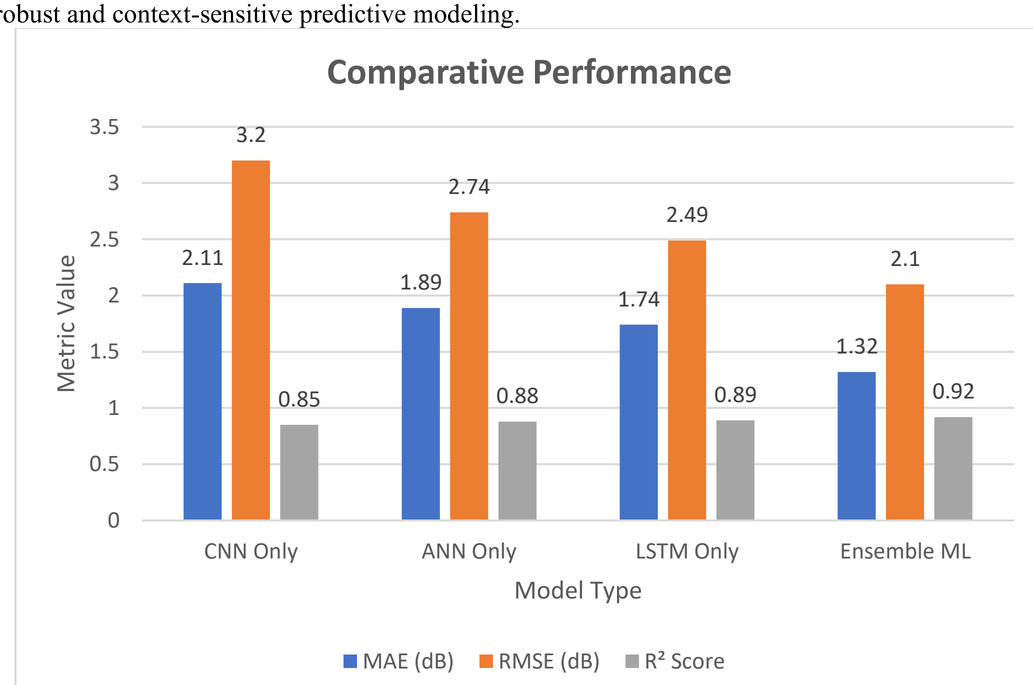

Figure 3: Comparative Performance of Individual and Ensemble Models

In Figure 3, the performance of the individual model is compared with that of the proposed ensemble model. Both models MAE, RMSE, and R^2 score metrics are measured and the ensemble model is shown to outperform all single models. It achieved the lowest error while maintaining the highest correlation compared to the actual signal behavior. These results suggest that the best hybrid models which utilize both spatial pattern recognition and temporal sequencing outperform other models. This is attributed to the model's better generalization. Overall, the ensemble configuration guarantees robust and scalable predictions in urban deployments.

These results confirm that the proposed ensemble learning framework effectively captures real-time urban signals. The dataset was structured as a hybrid dataset, which enabled the precise learning of relevant propagation features and spatial-temporal correlations. Deep learning models have lacked ensemble multi-perspective learning, which is evident in the ensemble's accuracy surpassing that of standalone models by a large margin. The assessment chart illustrates the benefits of utilizing multiple neural networks to enhance accuracy and stability. This, along with dataset design, model structure, and evaluation proves that the approach provides a robust framework for urban wireless signal prediction.

V. CONCLUSION

This research develops a novel ensemble learning approach for modeling millimeter-wave (mmWave) and terahertz (THz) signal propagation in urban settings. The inclusion of CNN, ANN, and RNN-LSTM models enables the system to learn profoundly from its spatial- and time-varying signals, thereby improving predictive performance. Addressing traditional model limitations, the proposed method, which utilizes real-world urban data and emphasizes critical spatial features such as construction materials, line of sight (LOS) conditions, and urban density, effectively addresses the dynamic real-time model challenges. Due to its adaptability and modularity, it can be implemented in various city landscapes and even future network benchmarks, including 6 G networks.

Alongside predictive performance, the model also focuses on SHAP and permutation importance to highlight key insights into signal propagation, thereby broadening its interpretability scope. The ensemble accuracy, alongside the ensemble's evaluation metrics — MAE, RMSE, and R^2 — confirms its performance and generalization capabilities. Coupled with its dependability and responsiveness, this system will greatly enhance infrastructure planning and optimization for urban wireless networks, including antenna positioning and real-time adaptive communication algorithms. This work integrates physical models with intelligent algorithms, thereby advancing the design of wireless communication systems.

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