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Dust Storm Attenuation Prediction Using a Hybrid Machine Learning Model Based on Measurements in Sudan

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ABSTRACT Sand and dust storms significantly challenge microwave and millimeter-wave communications, particularly in arid and semi-arid regions. Various models have been developed to predict attenuation caused by these storms theoretically and empirically based on two meteorological parameters, namely visibility and humidity. However, these models are found unable to predict most of the attenuation measurements. This study presents a hybrid Machine Learning (ML) model that predicts dust storm attenuation for 22 GHz terrestrial links using meteorological data. The received signal levels were measured for a 22 GHz link over a month in Khartoum, Sudan. The visibility, humidity, atmospheric pressure, temperature and wind speed were also monitored simultaneously by Automatic Weather Station (AWS). The proposed model incorporates XGBoost for feature selection and combines Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) layers to capture both short-term and long-term dependencies in meteorological data. The results demonstrate a strong correlation between meteorological parameters and dust storm attenuation. The model's performance is validated against the measured data at 22 GHz, outperforming existing empirical and theoretical models. The RMSE for the proposed model is 0.07, while all existing theoretical and empirical models are higher than 0.25. Furthermore, the proposed model demonstrates significant enhancements over the available ML model for dust attenuation prediction. This hybrid ML approach offers a more accurate and robust solution for predicting microwave and millimetre wave attenuation during dust storms, enhancing the reliability of communication systems in affected regions.

INDEX TERMS Dust Storm Attenuation, Microwave Propagation, Meteorological Parameters, Terrestrial Communication, Machine Learning, XGBoost, LSTM, GRU.

I. INTRODUCTION

Severe weather phenomena known as sandstorms (haboob) are frequently seen in dry semi-arid and nearby arid areas. The prevalence of sandstorms is dependent upon both human activity and natural climate. Dust storms are common in many parts of the world, such as North Africa, the Middle East, Southwestern North America, the Northwest Chain, and arid parts of India [1].

Dust and sand storms result from temperature and air pressure differences between tropical regions with warm climates and high-altitude regions with cold climates. Strong winds produced from these differences may cause sand and dust particles to be lifted into the skies. The wind speed is directly related to the quantity of sand and dust particles the wind carries. Additionally, the relative humidity that is accompanied by the presence of abundant water resources and verdant vegetation along the wind's path rises. Dust storms are therefore complex phenomena involving a wide range of atmospheric elements. In recent studies, it has been extrapolated that Sudan and American dust storms often appear in the wet season, followed by thunderstorms. Whereas dust storms in other parts of the world appear frequently in the dry season [1], [2].

Dust storms have wide impacts on human health, transportation and communication systems. The risks to human health include respiratory and cardiovascular problems while transportation systems face hazardous driving conditions, long delays or cancellations of flights and infrastructure damage. Communication systems may suffer from severe signal attenuation which may break the link during the storm [3]. Recently, migration to the 5th and 6th generations of mobile communication has provided high bandwidth relying on millimeter waves. Previously, dust storm intensity was measured by dust concentration in cubic meters which was difficult to measure precisely. Fortunately, in recent years dust storms can be measured with visibility reduction. Moderate dust storms are classified with optical visibility ranging from 1000 m to 500 m, while a severe dust storm is when the visibility is less than 500 m [3][4].

Relative humidity has been observed to accompany sand and dust storms based on the currently available literature. The moisture content of dust's dielectric constant can be directly impacted by an apparent shift in relative humidity during a storm, which will significantly reduce the signal power because of modifications to the properties of the dust particles. Elsheikh et al. found that during a dust storm relative humidity increases from 20% to 70%. The dramatic increase in relative humidity has directly affected the dust particle dielectric constant and consequently degraded the signal significantly [3]. Moreover, Elsheikh *et al* have studied the effect of the humidity on sand and dust storm attenuation prediction. Humidity was observed to be higher during the dust storm events [3]. The available models are used to incorporate the effect of the humidity in the dielectric constant. The predicted attenuation using humid dielectric constant is much higher than the predicted attenuation using dry dust conditions. Eltahir *et al.* concluded from measurement that dust particles have irregular shapes [5]. A. Musa *et al.* have discussed the effect of canting angle on signal attenuation and cross-polarization during the dust storm. Wind turbulence during storms also affects the orientation angle of falling dust particles which describes the orientation of a particle's axis of symmetry (or revolution). Falling dust particles in the air may be subjected to wind shear and turbulence, which could cause canting angles and oscillations. However, A. Musa *et al.* have attempted to model these effects by relying on approximations; the actual dust particle has an irregular shape, which is difficult to model [6]. In addition, the effect of rapid change in temperature and atmospheric pressure accompanied by the dust storm on signal attenuation has not yet been studied [7]. Shamim et al. have applied ML techniques using data measured over one month. Their machine-learning prediction model used all meteorological features to provide good agreement. Furthermore, they employed Pearson's Correlation Coefficient (r) to evaluate the relationship between meteorological parameters and microwave signal attenuation. Their analysis highlighted the significance of incorporating multiple input features to enhance the accuracy of predictions for microwave signal attenuation [8]. Dust storms in Khartoum significantly affected the received signal level. These slow-moving, turbulent events disrupted weather stations and communication links, though parameters generally returned to normal afterward [7]. Signal drops were aligned with changes in pressure, visibility, and temperature, while wind speed and humidity exhibited opposite trends. Visibility and humidity were key factors, with the latter altering the properties of dust particles. Shamim et al. [8] emphasized the importance of incorporating multiple meteorological features to improve the accuracy of microwave signal attenuation predictions.

A recent research endeavor has explored the impact of sand and dust storms on electromagnetic wave propagation within communication networks. The results presented a statistical model correlating attenuation, frequency and visibility, utilizing NASA data dedicated to the Gulf region. The study compared the attenuation effects caused by sandstorms with those from rain and gaseous absorption, offering valuable insights into how various atmospheric conditions influence communication network performance [9].

From the available literature, prediction models can be classified into mathematical, empirical and machine-learning models. Mathematical models are based on certain assumptions to ease the complex computation of signal propagation based on Maxwell's equations analytically or numerically [10], [11], [12], [13], [14]. Two empirical models have been developed based on long-term measurements. These models are the first models to investigate and incorporate the relative humidity into the attenuation prediction formula [3],[5],[14]. Despite significant progress in predicting microwave signal attenuation due to dust and sandstorms. However, many existing models still face limitations. Traditional empirical and mathematical models, often rely on simplifying assumptions that hinder their ability to fully capture the complex atmospheric interactions involved. These models typically struggle to account for rapid fluctuations in temperature, atmospheric pressure, humidity, wind speed and the irregular shapes of dust particles, leading to inaccuracies in predicting attenuation. While some empirical models attempt to incorporate humidity and other meteorological factors, they lack the dynamic adaptability needed for more precise predictions.

ML model improves the prediction of micro- and millimeter wave attenuation by effectively capturing

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complex relationships within meteorological data and signal attenuation. Its capability to process high-dimensional data and adapt to new information enhances accuracy and provides valuable real-time insights, making it particularly suited for telecommunications applications. For time-series data, where data points are ordered and dependent on previous time steps, machine learning models must consider the temporal relationships between observations. Recurrent Neural Networks (RNNs) are particularly useful for such tasks. More advanced versions of RNNs, like LSTM and GRU networks, are designed to capture these dependencies by maintaining a memory of past data points, making them effective in sequential prediction tasks.

In recent years, many studies have applied deep learning techniques to improve the performance of time-series predictions in complex domains [15][16]. Traditional models often struggle to capture long-term dependencies in sequential data. For example, early traffic prediction models relied on simple time-based data, such as past speed or congestion levels from the previous few seconds, to predict future traffic states [17]. However, these models were limited in their ability to determine which past states were most relevant, leading to sub optimal predictions.

To address this limitation, Fernandes *et al.* [18] introduced combined LSTM networks for traffic flow forecasting, demonstrating that LSTMs can effectively predict traffic flow for multiple future time steps by addressing key model aspects such as input features and time frames. Haque *et al.* [19] demonstrated that hybrid models like GRU-LSTM outperform single-layer models in high-resolution temperature forecasting by capturing both short-term and long-term trends, with GRU proving consistently robust across diverse locations. Similarly, Hossain *et al.* [20] combined convolution neural networks (CNN), GRU, and fully connected neural networks for wind energy generation forecasting, demonstrating that hybrid architectures can effectively capture both short-term fluctuations and long-term trends. The proposed approach outperformed traditional models such as neural networks (NN), RNN, and LSTM, achieving significantly higher performance in short-term wind power predictions.

These results underscore the strength of LSTM and GRU models in managing complex, nonlinear, and high-dimensional data, making them powerful tools for time-series prediction tasks across a variety of domains.

Shamim *et al.*'s study presented a machine learning approach for predicting microwave signal attenuation during dust storms, achieving some success but also facing significant limitations [8]. However, their model relied on a basic regression-based method, which struggled to capture the temporal dependencies in meteorological data, such as the dynamic fluctuations in humidity and visibility over time. Additionally, by including all available meteorological features without adequate filtering, the model became susceptible to noise, which ultimately diminished its predictive accuracy. This underscores the need for more advanced techniques that can better handle complex interactions among features and temporal variations in the data.

This work contributes to the enhancement of micro and millimeter wave attenuation prediction during dust storms by introducing a hybrid ensemble machine learning model. It integrates XGBoost for feature selection with LSTM and GRU layers to effectively capture temporal patterns. By focusing on critical meteorological variables such as visibility, humidity, atmospheric pressure, temperature, and wind speed, the model aims to provide more accurate and robust predictions of signal attenuation, particularly in arid regions often impacted by dust and sandstorms. This hybrid ensemble ML approach addresses the limitations of prior empirical and ML models, improving prediction performance through advanced pre-processing and adaptive learning techniques. As a result, it presents reliable attenuation predictions based on meteorological and signal attenuation data, further enhancing our understanding of microwave signal behavior in challenging atmospheric conditions.

The remaining sections of this paper are organized as follows: Section 2 details the experimental methodology, including the data collection process, data pre-processing techniques, and the ML work flow. Section 3 presents the correlation analysis between meteorological parameters and microwave signal attenuation, followed by the ML model's training, validation, and test results for the proposed prediction. Furthermore, provides an in-depth discussion, comparing the proposed hybrid model's performance against existing models, highlighting its strengths in handling sequential data and feature selection. Finally, Section 4 concludes the study and outlines possible directions for future research.

II. METHODOLOGY

This section presents the proposed methodology for predicting microwave signal attenuation using a hybrid XGBoost, LSTM and GRU model. The methodology begins with Data Measurement, detailing the collection of meteorological data and the setup of the communication link. Following this, we describe the process of Signal Attenuation Calculation, explaining how the signal loss during sand and dust storms is computed. The methodology further covers data preprocessing techniques, feature selection using XGBoost [21], and the architectural design of the model, which integrates LSTM [22]-GRU [23] layers for sequential learning. Additionally, we outline steps taken to handle missing data, normalize features, and optimize model performance, ensuring robust predictions under diverse meteorological conditions.

A. DATA COLLECTION

Figure 1 shows the location of the climate conditions measuring equipment and a microwave link in Khartoum, Sudan, based on the analysis of the one-year data collected from May 31, 2014, to June 1, 2015 [3], it was found that nearly one-third of the dust and sand storms occurred between June 1, 2014, and July 3, 2014. Consequently, only

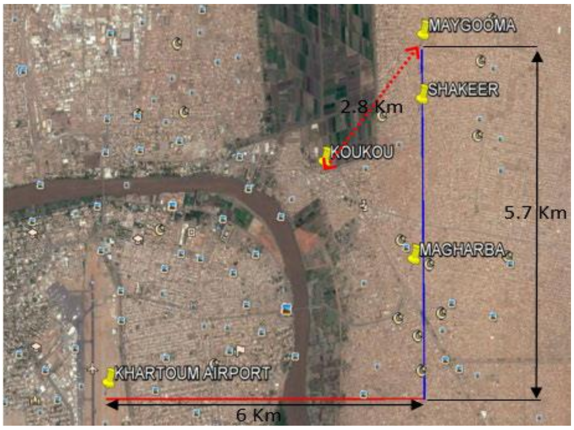

Figure 1: Location map of microwave links and Automatic Weather Station in Khartoum

the data from this specific period (June 1 to July 3, 2014) was utilized for training the ML model. The microwave link, operated by MTN's mobile operator company, Sudan branch, is known as the Maygoma-Kouku link. This link operates at a frequency of 21.3 GHz with a path length of 2.8 km. Both antennas are vertically polarized, with diameters of 0.6 meters, gains of 40.5 dBi, and a transmitted power of 11 dBm. The Maygoma antenna has a height of 17 meters, while the Kouku antenna is positioned at 24 meters. The link is situated about 5 km from the Khartoum Airport meteorological station, which is equipped with a Vaisala transmissometer for measuring visibility within a range of 10 to 10,000 meters.

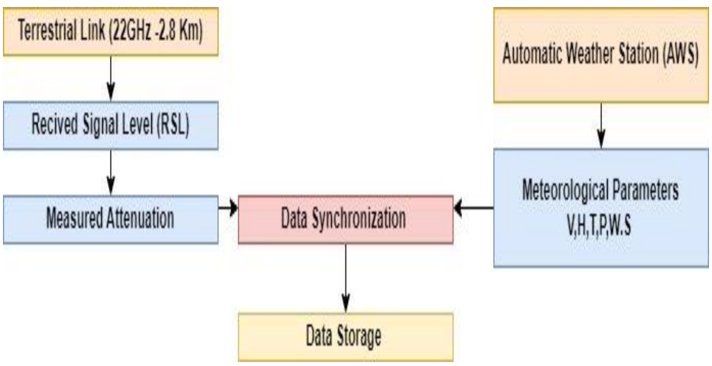

Figure 2: Block diagram explaining the process of data collection

The microwave link specifications, including RX frequency, antenna gain, and transmission power, are summarized in Table 1.

The meteorological station also features sensors that measure relative humidity, atmospheric pressure, temperature, and wind speed. The HMP155 sensor reliably tracks both humidity and temperature, while the LT31 sensor measures the visibility offering insights into fog and dust storm conditions. Additionally, the WMT52 sensors

TABLE 1
MICROWAVE LINK SPECIFICATIONS

Parameter	Unit	Maygooma	Koukou
RX Frequency	MHz	22488.25	21288.25
Polarization		Vertical	Vertical
Antenna Diameter	m	0.6	0.6
Antenna Gain	dBi	40.50	40.50
Antenna Height	m	17	24
TX Power	dBm	11.5	11.5

monitor wind speed and direction, providing a comprehensive view of the environmental conditions. The Vaisala BAROCAP® PTB330 provides ±0.10 hPa accuracy across a 500–1100 hPa range, with ±0.1 hPa temperature dependency from -40°C to +60°C.

The received signal level of the selected microwave link was analyzed to compute the attenuation in dB/km, a critical parameter for assessing and predicting microwave link performance. Figure 2 illustrates the overall data collection and synchronization process, combining meteorological parameters from the Automatic Weather Station and signal measurements from the terrestrial microwave link. Attenuation is preferred over the received signal level as it provides a more standardized and reliable measure for comparison. During clear weather conditions, the received signal level was observed to be -43.8 dBm, which was used as the reference signal level for further calculations. The absolute values of the received signal levels from the selected data were calculated and subtracted from the reference level to determine the total attenuation in dB. This total attenuation was then divided by the microwave link length of 2.8 km to calculate the specific attenuation in dB/km [3]. The collected meteorological data, as summarized in Table 2, shows a wide range of environmental conditions observed during the study. Optical visibility ranged from 100 to 10,000 meters, with an average of 8,688.04 meters and a standard deviation of 2,461.87 meters, reflecting varying dust storm intensities. The temperature fluctuated between 25.1°C and 44.7°C, averaging 35.68°C with a standard deviation of 4.13°C. Relative humidity values spanned from 6% to 74%, with a mean of 21.57% and a standard deviation of 13.87%, indicating substantial variability in moisture levels. Atmospheric pressure ranged narrowly between 958.5 and 967.8 Pa, averaging 963.8 Pa with a small standard deviation of 2.12 Pa. Wind speed varied from calm conditions to 35.57 knots, averaging 9.40 knots with a 4.08-knot standard deviation. Lastly, signal attenuation due to dust storms ranged from 0.107 to 3.357 dB/km, with a mean attenuation of 0.660 dB/km and a standard deviation of 0.192 dB/km, highlighting significant variations in the impact of dust storms on signal strength.

B. DATA PREPROCESSING

Data pre-processing is a critical step that ensures the model's robustness and improves its predictive accuracy.

TABLE 2
WEATHER STATION SPECIFICATIONS

Feature	Min.	Max.	Mean	Sd.
Optical Visibility (m)	100	10000	8688.03	2461.87
Temperature (C^0)	25.1	44.7	35.683	4.130
Relative Humidity (%)	6	74	21.57	13.867
Atmospheric Pressure (Pa)	958.5	967.8	963.8	2.123
Wind Speed (Knots)	0	35.57	9.398	4.079
Attenuation (dB/km)	0.107	3.357	0.660	0.192

The following steps were carefully applied to prepare the dataset:

1) Handling of Missing Data

Missing data values in the dataset were addressed using linear interpolation. This technique estimates missing values based on adjacent data points, preserving the continuity and consistency of the time-series data. This method is essential for sequential models like LSTM and GRU, which rely on smooth temporal transitions for accurate forecasting. By filling in gaps without introducing biases, the model can better learn from the full dataset, ensuring that no information is lost.

Linear interpolation is based on the Straight-Line equation (1):

$$y + y_1 = \frac{(x-x_1).(y_2-y_1)}{(x_2-x_1)} \tag{1}$$

Where (x_1, y_1) and (x_2, y_2) are the known data points. x is the point at which you want to estimate the value of y. And y is the interpolated value at x.

2) Normalization

All features were normalized using *Standard Scaler as shown in equation* (2) to standardize the input data. This transformation ensures that each feature has a mean of 0 and a standard deviation of 1, which is crucial for models involving gradient-based optimization. Normalization prevents features with larger numeric ranges (such as temperature or wind speed) from disproportionately influencing the model's training process [24]. As a result, the model treats all input variables equally, allowing it to converge faster and perform more efficiently. One of the best performance normalization is

Standard Scaler formula is:

$$z = \frac{x-\mu}{\sigma} \tag{2}$$

Where z is the normalized value, x is the original data point, μ is the mean of the data, and σ is the standard deviation of the data.

The Standard Scaler formula is directly addresses the problem of the features (temperature, wind speed, visibility humidity, pressure) with varying numeric ranges by normalizing them to a common mean and standard deviation. This normalization ensures that all features are treated equally by the model, which is essential for gradient-based optimization methods such as gradient descent. By normalizing data, models can achieve faster convergence, improved performance, and more stable training processes.

3) Dataset Split

The dataset was split into a 90% training set (35,140) and a 10% test set (3,905), following best practices in machine learning for evaluating model performance. This split allows the model to be trained on the majority of the data while reserving a portion for testing, thus ensuring the model is evaluated on unseen data. This split is key for assessing the generalization capability of the model, providing a realistic estimate of its performance in real-world conditions.

4) Cross-Validation

To further ensure the robustness of the model and reduce the likelihood of over fitting, *k*-Fold Cross-Validation (CV) was applied [25]. This method divides the training data into 10 folds training the model on 9 folds while validating it on the remaining fold. The process is repeated 10 times, each time with a different validation fold. The final model's performance is averaged across all 10 iterations, providing a reliable measure of how well the model performs across different subsets of the data. CV significantly reduces bias and variance in model evaluation, ensuring that the results are not skewed by any particular dataset split [26], [27].

C. MODEL ARCHITECTURE

The proposed model is a hybrid ensemble that combines XGBoost, LSTM, and GRU layers. This architecture was specifically chosen for its ability to manage both feature selection and temporal dependencies, making it highly effective for predicting microwave signal attenuation under varying meteorological conditions. As shown in Figure 3, the model begins with data preprocessing, where missing values are handled through interpolation, and the data is normalized to ensure consistent scaling across all features. The preprocessed data is then passed to the XGBoost algorithm, which ranks and selects the most significant meteorological features, such as visibility, humidity, and temperature. These selected features are input into a sequential model that consists of an LSTM layer followed by a GRU layer, both of which are used to capture the short-term and long-term temporal dependencies in the data. The architecture is designed for optimal efficiency and accuracy. Dropout layers are applied after each recurrent layer to prevent over fitting, and a final Dense layer with 100 units and the Rectified Linear Unit (ReLU) activation function is used for the output. The model is trained using the Adam optimizer with a learning rate of 0.001, and performance metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE) are tracked throughout the training process, as shown in Table 3.

1) Rationale Behind the Model

XGBoost is known for its exceptional performance in ranking features by importance, making it ideal for feature selection in complex datasets. XGBoost's ability to assess the contribution of each feature to the model's predictive power enables the identification of the most relevant variables, significantly enhancing the model's overall efficiency. By leveraging XGBoost's advanced gradient boosting algorithms, practitioners can effectively identify and retain the features that have the greatest impact on the target variable, thereby reducing the inclusion of irrelevant or noisy data that could hinder model performance. This process of feature selection not only simplifies the model but also improves its interpretability, making it easier to understand the relationships between the selected features and the predictions [28][29].

The most significant meteorological factors which are visibility, humidity, temperature and wind speed are included in the prediction model. This method reduces noise by excluding irrelevant variables, leading to improved model performance and faster computation. Furthermore, XGBoost is highly efficient and scalable, handling large datasets with ease while providing interpretable results about feature significance. This efficiency is crucial when working with high-dimensional meteorological data, as it prevents over fitting and ensures the model remains computationally manageable. Meteorological conditions that influence microwave signal attenuation are dynamic and evolve over time, making LSTM and GRU layers ideal choices for capturing these temporal relationships. LSTM layers are particularly good at learning long-term dependencies, where past atmospheric conditions (such as prolonged humidity or temperature changes) have lasting effects on signal attenuation. GRU layers, while similar to LSTMs, offer a more computationally efficient solution by simplifying the internal structure, reducing the number of parameters while maintaining comparable performance.This combination of LSTM and GRU ensures that the model not only learns short-term variations (such as sudden changes in wind speed or visibility during a storm) but also captures longer-term trends (such as gradual shifts in pressure or humidity) that could impact signal strength.
The hybrid integration of XGBoost with LSTM and GRU offers a theoretically advantage approach by leveraging the strengths of each component. XGBoost excels in feature selection, isolating the most significant meteorological variables while reducing noise and improving model interpretability. LSTM layers effectively capture long-term dependencies in sequential data, such as sustained humidity changes, while GRU layers handle short-term variations, like sudden drops in visibility or spikes in wind speed, with greater computational efficiency. This synergy ensures a robust balance between accurate feature extraction and temporal pattern recognition, outperforming traditional machine learning models and hybrid architectures like CNN-GRU or standalone LSTM-GRU combinations, particularly in handling complex dynamic atmospheric data [30].

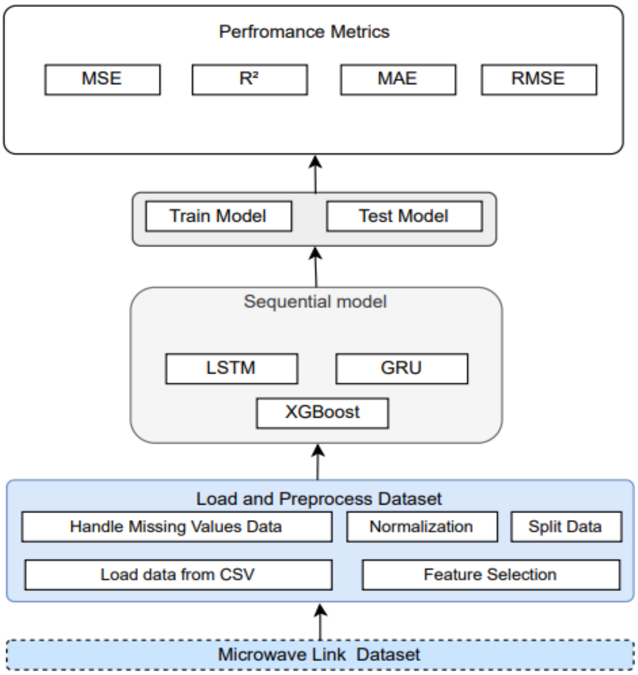

Figure 3: Schematic Representation of the Hybrid XGBoost-LSTM-GRU Model Architecture for Microwave Signal Attenuation Prediction.

As described in Algorithm 1, the overall model structure combines the strengths of feature selection and temporal learning to provide robust predictions of microwave signal attenuation.

Algorithm 1: Hybrid XGBoost-LSTM-GRU for Signal Attenuation Prediction

1. **Input**: Preprocessed meteorological dataset
2. **Output**: Predicted signal attenuation (dB/km)
3. *Data Preprocessing:*
   (a) Handle missing data using linear interpolation.
   (b) Normalize features using Standard Scaler.
   (c) Split dataset into training (90%) and testing (10%) sets.
   (d) Apply 10-fold CV to the training data.
4. *Feature Selection (XGBoost):*
   (a) Train XGBoost model with hyperparameters:
      - n estimators = 300
      - learning rate = 0.1
      - max depth = 10
   (b) Rank features based on importance and select the most relevant meteorological variables.
5. *Model Construction:*
   (a) Input selected features to an LSTM layer with 128 units.
   (b) Add a GRU layer with 128 units.
   (c) Apply Dropout (rate = 0.2) after each recurrent layer.
   (d) Add a Dense layer with 100 units (ReLU activation) for output.

6. *Model Training:*
   (a) Train the model using the Adam optimizer with learning rate = 0.001.
   (b) Use MSE as the loss function.
   (c) Track MAE and RMSE during training.
7. *Model Evaluation:*
   (a) Evaluate the model on validation and test sets using MAE, RMSE, and R^2 metrics.
   (b) Generate training and validation loss/error plots across epochs.
8. **Output**: Predicted signal attenuation (dB/km) for the test set.

2) Experimental Setup

The experiment setup involves the utilization of Keras (version 2.14.0) [31] and TensorFlow (version 2.14.0) [32] (version 2.14.0), both of which are integrated into the Visual Studio Code (VSCode) environment. This configuration facilitates a streamlined development process, allowing for efficient model building and training. Keras [31] serves as a high-level API for constructing neural networks, leveraging Tensor Flow as its backend to perform the heavy lifting of computations. By maintaining these specific versions, the experiment aims to ensure compatibility and leverage the latest features and improvements offered by these frameworks, thereby enhancing the overall performance and reliability of the ML models being developed. All data preprocessing stages, model training, hyper parameter tuning, and model evaluation were performed using this platform. Hyper parameters were selected using a grid search approach, testing various combinations of learning rates, batch sizes, and activation functions to identify the optimal configuration for the model. The results of this search informed the final parameters used for training, ensuring a balance between performance and computational efficiency.

To identify the most relevant features, XGBoost was used for feature selection. The top-ranked meteorological features were then fed into a sequential model, which integrated LSTM and GRU layers for capturing temporal dependencies in the data. This hybrid model architecture was designed to capture both short-term variations (such as sudden drops in visibility or spikes in humidity during dust storms) and longer-term weather trends. The model was trained for 100 epochs, with key performance metrics such as loss MSE, MAE, and RMSE tracked at each epoch [33]. Hyper parameter tuning was conducted using a random grid search to optimize the model [34], focusing on minimizing the loss function.

The performance of the model was evaluated using several regression metrics, which provided a detailed understanding of how well the model predicted microwave signal attenuation under varying meteorological conditions. These metrics included:

Mean Absolute Error (MAE): This metric measures the average magnitude of the errors in the predictions, providing a straightforward interpretation of how close the predicted values are to the actual values as shown in equation (3).

TABLE 3
COMMON SPECIFICATIONS

Category	Name	Value
CV	Fold size	10
	Shuffle	True
	Random state	1
XGBoost Layer	# of estimators	100
	Learning rate	0.1
	Maximum depth	10
	Subsample	0.8
	Column sample by tree	0.8
LSTM Layer	Units	128
	Activation function	tanh
GRU Layer	Units	128
	Activation function	tanh
Dense Layer	Dense units	100
	Activation function	ReLU
Model Parameters	Dropout rate	0.2
	Batch size	48
	Epochs	100
	Learning rate	0.001

$$MAE=\frac{1}{nT}\sum_{i=1}^{nT}|p_i-a_i| \quad (3)$$

Mean Squared Error (MSE): MSE is used as the primary loss function for the model. It calculates the average squared difference between predicted and actual values, penalizing larger errors more heavily as shown in equation (4).

$$MSE=\frac{1}{nT}\sum_{i=1}^{nT}(p_i-a_i)^2 \quad (4)$$

Root Mean Squared Error (RMSE): The square root of the MSE, RMSE is useful as it provides an error metric that is on the same scale as the original target variable (signal attenuation). This metric is particularly useful when we want to evaluate the model's prediction errors in a more interpretable way as shown in equation (5).

$$RMSE=\sqrt{\frac{1}{nT}\sum_{i=1}^{nT}(p_i-a_i)^2} \quad (5)$$

Coefficient of Determination (R^2): This metric measures the proportion of variance in the target variable that is explained by the model. A higher R^2 value indicates that the model has captured a larger portion of the variance in the data as shown in equation(6).

$$R^2=1-\frac{\sum_{i=1}^{nT}(a_i-p_i)^2}{\sum_{i=1}^{nT}\left(a_i-\underline{a_i}\right)^2} \quad (6)$$

where p_i represents the predicted value, a_i represents the actual value and, nT number of training samples.

III. RESULTS AND ANALYSIS

In this section, we analyzed the performance of the proposed hybrid XGBoost-LSTM-GRU model in predicting microwave signal attenuation caused by adverse atmospheric conditions such as dust and sandstorms. The evaluation process involved 10-fold CV to ensure the model generalized well across the dataset and minimized overfitting. Tables 4, 5 and 6 provides an overview of the model's performance metrics across all 10 folds, including MAE, MSE, RMSE, and R^2 for the training, validation, and testing sets. The Training MAE values across the folds consistently remained at 0.020, indicating that the model learned the underlying patterns of the data without significant over fitting. The Training RMSE values ranged from 0.030 to 0.032, with a high average R^2 of 0.983, indicating that the model captured a large proportion of the variance in the training data. Validation results showed MAE values between 0.029 and 0.032, demonstrating that the model was able to generalize well to unseen validation data. The Validation RMSE values ranged from 0.056 to 0.087, with Validation R^2 scores between 0.786 and 0.904, indicating strong predictive performance even in the validation phase. In the Testing phase, the MAE values ranged from 0.030 to 0.031, while the RMSE values ranged between 0.065 and 0.076. The Test R^2 scores, which averaged 0.860, further confirmed that the model consistently minimized prediction errors and performed well on unseen test data. The model was trained for 100 epochs with a batch size of 48 using the Adam optimizer. As shown in the training metrics, the training loss rapidly decreased during the first 10 epochs and gradually stabilized around 0.001, while the validation loss converged around 0.005. The consistent alignment between training and validation losses indicates that the model effectively learned the data patterns without over fitting. The MAE and RMSE values steadily declined across both the training and validation sets, with final MAE values around 0.031 for validation, demonstrating that the model's predictions closely matched actual values. Similarly, the RMSE values for the training set converged to 0.031, and for the validation set to 0.070, confirming that the model was well-optimized and generalized effectively to unseen data. The results confirm that the proposed model is suitable for predicting microwave signal attenuation under varying atmospheric conditions.

The average training and validation results of the model for MAE, MSE, and RMSE are shown in Figure 4 (a), (b), and (c), respectively. To further validate the proposed model, the Root Mean Square Error (RMSE) of the previous empirical and mathematical predictions was assessed using the ITU-R P.311-14 method [14]. The results were then compared with those of the proposed model for 22 GHz millimeter-wave links, as presented in Table 8. The comparison of performance metrics

TABLE 4 TRAINING RESULTS

No of Fold	MSE	MAE	RMSE	R^2
1	0.001	0.020	0.032	0.984
2	0.001	0.020	0.032	0.983
3	0.001	0.020	0.030	0.983
4	0.001	0.020	0.031	0.983
5	0,.001	0.020	0.030	0.983
6	0.001	0.020	0.031	0.983
7	0.001	0.020	0.031	0.983
8	0.001	0.020	0.031	0.984
9	0.001	0.020	0.031	0.983
10	0.001	0.020	0.031	0.984
Mean	0.001	0.020	0.031	0.983

TABLE 5 VALIDATION RESULTS

NO of Fold	MSE	MAE	RMSE	R^2
1	0.003	0.029	0.056	0.904
2	0.004	0.031	0.064	0.898
3	0.007	0.032	0.085	0.841
4	0.004	0.031	0.063	0.892
5	0.005	0.032	0.072	0.860
6	0.004	0.031	0.064	0.894
7	0.006	0.032	0.079	0.846
8	0.008	0.032	0.087	0.786
9	0.005	0.031	0.067	0.866
10	0.005	0.031	0.073	0.846
Mean	0.005	0.031	0.071	0.863

underscores the advantages of the proposed model over existing empirical and mathematical methods. Previous studies, such as those by Goldhirsh *et al.* [32]. and Ahmed *et al.* [10], reported high RMSE values exceeding 2, indicating substantial prediction errors. In contrast, the proposed model achieved an RMSE of 0.070, demonstrating significantly greater accuracy. Although models like those by Eltahir *et al.* [14]. accuracy. Although models like those by Eltahir *et al.* [14]. and Elfatih *et al.* [3] had lower RMSE values (0.22 and 0.26), they lacked comprehensive evaluation metrics. Additionally, the proposed model's R^2 value of 0.860 further validates its strong predictive capability, highlighting its effectiveness in forecasting microwave signal attenuation during dust storm

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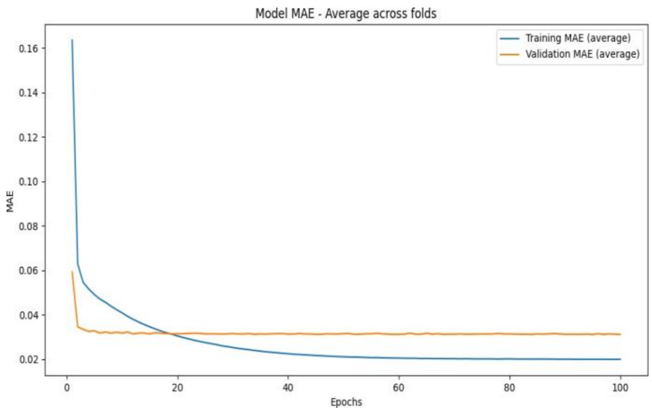
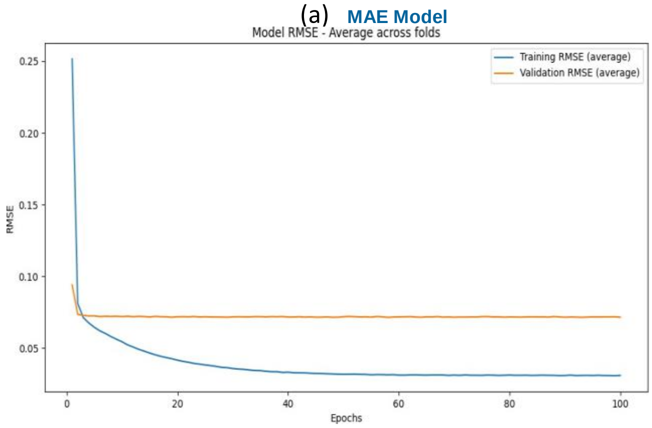
TABLE 6 TEST RESULTS

No of Fold	MSE	MAE	RMSE	R^2
1	0.005	0.030	0.068	0.867
2	0.005	0.031	0.069	0.861
3	0.006	0.031	0.076	0.833
4	0.005	0.031	0.070	0.857
5	0.004	0.031	0.065	0.877
6	0.005	0.031	0.070	0.859
7	0.005	0.031	0.068	0.868`
8	0.005	0.031	0.068	0.866
9	0.005	0.031	0.068	0.865
10	0.005	0.030	0.072	0.849
Mean	0.005	0.031	0.070	0.860

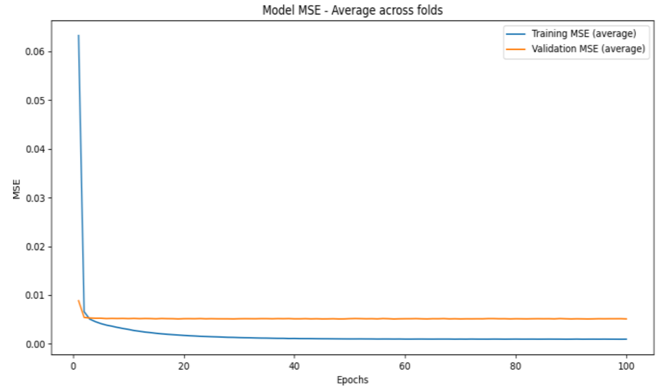
Additionally, in the ablation study, the proposed model demonstrated strong performance across various metrics compared to the only available ML model for predicting attenuation during dust storms at 22 GHz, as shown in Table 7. The comparison of performance metrics between Shamim et al.'s model and the proposed hybrid model reveals notable improvements in predictive accuracy.



(a) **MAE Model**



(b) RMSE Model



(c) MSE Model

Figure 4: Performance Metrics (MAEW,RMSEand MSE) of the model

The proposed model achieved a training MAE of 0.001, an RMSE of 0.031, and an R^2 of 0.983, significantly surpassing Shamim et al. [8] results, which included an MAE of 0.0285, an RMSE of 0.0751, and an R^2 of 0.847. During the validation phase, the proposed model also performed well, recording a MAE of 0.005 and an RMSE of 0.071, while Shamim et al. had a MAE of 0.0277 and an RMSE of 0.0725. Although test metrics for Shamim *et al.* [8] were not available, the proposed model continued to demonstrate its effectiveness with a MAE of 0.005 and an RMSE of 0.070.

Overall, the proposed model demonstrates good and consistent performance, underscoring its value in predicting micro and millimeter wave signal attenuation during dust storms. These results further highlight the efficacy of the proposed hybrid model, particularly its ability to capture complex, time-dependent meteorological factors impacting signal attenuation.

Advanced feature selection (XGBoost) and temporal modeling (LSTM-GRU) contribute to the model's good performance over traditional methods. Moreover, incorporating ensemble learning methods enhances the model's adaptability and ensures better generalization to new, unseen data.

The developed hybrid XGBoost-LSTM-GRU model in this study significantly improves predictions of micro- and millimeter wave signal attenuation during dust and sandstorms. By using XGBoost for feature selection, it effectively isolates key meteorological variables like visibility, temperature, wind speed, and humidity, thereby reducing noise in high-dimensional datasets. This targeted approach surpasses the feature identification methods employed in previous ML model-based studies [8], which often lack advanced techniques like stepwise elimination. The model's integration of LSTM and GRU layers captures both long-term dependencies and short-term variations of meteorological parameters and their impacts on signal attenuation, enabling it to adapt to rapidly changing conditions during dust storms.

TABLE 7

PERFORMANCE COMPARISON AND ABLATION STUDY OF MACHINE LEARNING MODELS

Model	MAE	MSE	RMSE	R^2
Training Performance Metric				
Shamim *et al.* [8]	0.029	0.006	0.075	0.847
XGBoost	0.078	0.013	0.113	0.661
LSTM	0.070	0.012	0.108	0.748
GRU	0.072	0.012	0.111	0.731
XGBoost + LSTM	0.030	0.002	0.046	0.975
XGBoost + GRU	0.031	0.002	0.047	0.977
Proposed Model	0.001	0.020	0.031	0.983
Validation Performance Metric				
Model	**MAE**	**MSE**	**RMSE**	**R^2**
Shamim et al. [8]	0.028	0.005	0.073	0.852
XGBoost	0.081	0.015	0.122	0.601
LSTM	0.064	0.011	0.104	0.708
GRU	0.065	0.012	0.108	0.681
XGBoost + LSTM	0.034	0.006	0.074	0.853
XGBoost + GRU	0.034	0.005	0.072	0.859
Proposed Model	0.005	0.031	0.071	0.863
Test Performance Metric				
Model	**MAE**	**MSE**	**RMSE**	**R^2**
Shamim *et al.* [8]	NA	NA	NA	NA
XGBoost	0.077	0.013	0.116	0.612
LSTM	0.062	0.009	0.097	0.730
GRU	0.063	0.010	0.099	0.720
XGBoost + LSTM	0.032	0.004	0.071	0.856
XGBoost + GRU	0.033	0.005	0.072	0.856
Proposed Model	0.005	0.031	0.070	0.860

TABLE 8
COMPARISON OF RMSE AMONG EMPIRICAL, MATHEMATICAL, AND PROPOSED MODELS

Model	RMSE
Goldhirsh *et al.* [14],[35]	5.99
Ahmed *et al.* [14],[10]	5.82
Zain *et al.* [14],[36]	4.41
Sharif *et al.* [14],[12]	4.49
Eltahir *et al.* [14]	0.22
Elfatih *et al.* [14],[8]	0.17
Proposed Model	0.07

Unlike traditional theoretical and empirical models that struggle with the physical complex characteristics of dust storms, this hybrid approach leverages machine learning's strengths to enhance predictive performance across diverse atmospheric conditions. Overall, the proposed model offers a robust framework for accurately modeling signal behavior during extreme weather events, paving the way for future research in this area. However this approach requires a large number of real time measurement data for the region where the model needs to be utilized. Data availability could be a challenge for accurate prediction.

IV CONCLUSION

Various models have been developed to predict attenuation caused by sand and dust storms theoretically and empirically based on two meteorological parameters, namely visibility and humidity. However these models are found unable to predict most of the attenuation measurements. The meteorological parameters and received signal strength of a 22 GHz microwave link in Khartoum, Sudan, were concurrently monitored over one month period. Variations in signal levels were analyzed in relation to atmospheric pressure, visibility, temperature, wind speed, and relative humidity. A hybrid ensemble model combines XGBoost for feature selection with LSTM and GRU layers for temporal learning was used to predict the dust storm attenuation. The analysis shows a strong correlation between meteorological parameters and dust storm attenuation. The model's performance is validated against the measured data at 22 GHz. The RMSE for the proposed model is 0.07, while that for all existing theoretical and empirical models are varied from 0.22 to 2.84. This hybrid machine learning approach offers a more accurate and robust solution for predicting microwave and millimeter wave attenuation during dust storms, enhancing the reliability of communication systems in affected regions. However this approach requires a large number of real time measurement data for the region where the model needs to be utilized. Data availability could be a challenge for accurate prediction. Future works will focus on expanding the dataset to include different geographic locations, enhancing the thereby improving the model's ability to generalize to other environmental conditions. Additionally, more advanced temporal models, such as transformers, are planned to be explored to further capture long-term dependencies.

REFERENCES

[1] Z. Gu et al., "An Overview of Triggering Mechanisms and Characteristics of Local Strong Sandstorms in China and Haboobs," *Atmosphere*, vol. 12, no. 6, p. 752, Jun. 2021, doi: 10.3390/ATMOS12060752.

[2] A. A. Arishi and A. A. Arishi, "Classification of Sandstorms in Saudi Arabia," *Atmospheric and Climate Sciences*, vol. 11, no. 1, pp. 177–193, Dec. 2020, doi: 10.4236/ACS.2021.111012.

[3] E. A. A. Elsheikh, M. R. Islam, M. H. Habaebi, A. F. Ismail, and A. Zyoud, "Dust storm attenuation modeling based on measurements in Sudan," *IEEE Trans. Antennas Propag.*, vol. 65, no. 8, pp. 4200–4208, Aug. 2017. doi: 10.1109/TAP.2017.2715369.

[4] E. A. A. Elsheikh et al., "Effect of dust storm intensity variations on total path attenuation prediction," *IEEE Trans. Antennas Propag.*, vol. 70, no. 4, pp. 2884–2890,

Apr. 2022. doi: 10.1109/TAP.2021.3138259.

[5] E. I. Eltahir, A. A. Elfatih Elsheikh, A. Awad Babiker, and K. H. Bilal, "10 GHz investigation of Sudanese dust event particles characteristics," *Proc. Int. Conf. Comput., Control, Electr. Electronics Eng.*, Sep. 2019, doi: 10.1109/ICCCEEE46830.2019.9071029. .

[6] A. Musa, M. F. Camara, A. H. Abdulla, S. O. Bashir, and S. M. A. Hamed, "Modeling of dust particles canting as input to microwave cross polarization," *Proceedings - 2015 International Conference on Computing, Control, Networking, Electronics and Embedded Systems Engineering, ICCNEEE 2015, pp. 87–90*, Jan. 2016, doi: 10.1109/ICCNEEE.2015.7381435.

[7] E.I. Eltahir, Elfatih A. A. Elsheikh, Md. Rafiqul Islam,Aisha.H Abduallah, Mohamad Hadi Habaebi, and Mosab Hamdan "Effects of Meteorological Parameters on Microwave Propagation Modeling During Dust Storm" *Proc. 9th International Conference on Mechatronics Engineering (ICOM'24) 2024* Kuala Lumpur, Malaysia 2024. .

[8] M. Z. M. Shamim, E. A. A. Elsheikh, F. E. M. S. Salih, and M. R. Islam, "Signal Attenuation Prediction Model for a 22 GHz Terrestrial Communication Link in Sudan Due to Dust and Sand Storms Using Machine Learning," *IEEE Access*, vol. 9, pp. 164632–164642, 2021, doi: 10.1109/ACCESS.2021.3132700.

[9] H. S. Cankurtaran, S. Yarkan, M. O. Hasna, and K. A. Qaraqe, "Statistical Modeling of Sand and Dust Storm Attenuation," *2022 International Balkan Conference on Communications and Networking, BalkanCom 2022*, pp. 95–99, 2022, doi:10.1109/BALKANCOM55633.2022.9900820.

[10] A. S. Ahmed, A. A. Ali, and M. A. Alhaider, "Airborne Dust Size Analysis for Tropospheric Propagation of Millimetric Waves into Dust Storms," *IEEE Transactions on Geoscience and Remote Sensing*, vol. GE-25, no. 5, pp. 593–599, 1987, doi: 10.1109/TGRS.1987.289838.

[11] H. Y. Chen and C. C. Ku, "Microwave and millimeter-wave attenuation in sand and dust storms," 2*012 19th International Conference on Microwaves, Radar and Wireless Communications, MIKON 2012*, vol. 2, pp. 527–532, 2012, doi: 10.1109/MIKON.2012.6233610.

[12] S. M. Sharif, "Attenuation properties of dusty media using mie scattering solution," *Progress In Electromagnetics Research M*, vol. 43, pp. 9–18, 2015, doi: 10.2528/PIERM15022403.

[13] H. Y. Chen and C. C. Ku, "Calculation of Wave attenuation in sand and dust storms by the FDTD and turning bands methods at 10-100 GHz," *IEEE Trans Antennas* Propag, vol. 60, no. 6, pp. 2951–2960, 2012, doi: 10.1109/TAP.2012.2194657.

[14] E. I. Eltahir et al., "Sand and Dust Storm Attenuation Prediction Using Visibility and Humidity Measurements," *IEEE Access*, vol. 12, pp. 79602–79612, 2024, doi: 10.1109/ACCESS.2024.3409576.

[15] B. Mahesh, "Machine Learning Algorithms-A Review," *Technical Report in International Journal of Science and Research*, 2019, doi: 10.21275/ART20203995.

[16] Z. Han, J. Zhao, H. Leung, K. F. Ma, and W. Wang, "A Review of Deep Learning Models for Time Series Prediction," *IEEE Sens J, vol. 21, no. 6, pp. 7833–7848*, Mar. 2021, doi: 10.1109/JSEN.2019.2923982.

[17] Y. Lv, Y. Duan, W. Kang, Z. Li, and F. Y. Wang, "Traffic Flow Prediction with Big Data: A Deep Learning Approach," *IEEE Transactions on Intelligent Transportation Systems*, vol. 16, no. 2, pp. 865–873, Apr. 2015, doi: 10.1109/TITS.2014.2345663.

[18] B. Fernandes, F. Silva, H. Alaiz-Moreton, P. Novais, J. Neves, and C. Analide, "Long Short-Term Memory Networks for Traffic Flow Forecasting: Exploring Input Variables, Time Frames and Multi-Step Approaches," *Informatica*, vol. 31, no. 4, pp. 723–749, Jan. 2020, doi: 10.15388/20-INFOR431.

[19] E. Haque, S. Tabassum, and E. Hossain, "A Comparative Analysis of Deep Neural Networks for Hourly Temperature Forecasting," *IEEE Access*, vol. 9, pp. 160646–160660, 2021, doi: 10.1109/ACCESS.2021.3131533.

[20] M. A. Hossain, R. K. Chakrabortty, S. Elsawah, E. Gray, and M. J. Ryan, "Predicting Wind Power Generation Using Hybrid Deep Learning with Optimization," I*EEE Transactions on Applied Superconductivity*, vol. 31, no. 8, Nov. 2021, doi: 10.1109/TASC.2021.3091116.

[21] T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," *Proc. ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining*, vol. 2016, pp. 785–794, Aug. 2016, doi: 10.1145/2939672.2939785.

[22]. Y. Yu, X. Si, C. Hu, and J. Zhang, "A review of recurrent neural networks: LSTM cells and network architectures," *Neural Comput.*, vol. 31, no. 7, pp. 1235–1270, Jul. 2019, doi: 10.1162/NECO_A_01199.

[23] R. Dey and F. M. Salemt, "Gate-variants of Gated Recurrent Unit (GRU) neural networks," *Midwest Symposium on Circuits and Systems*, vol. 2017-August, pp. 1597–1600, Sep. 2017, doi: 10.1109/MWSCAS.2017.8053243.

[24] L. B. V. de Amorim, G. D. C. Cavalcanti, and R. M. O. Cruz, "The choice of scaling technique matters for classification performance," *Appl. Soft Comput.*, vol. 133, p. 109924, 2023, doi: 10.1016/j.asoc.2022.109924.

[25] T.-T. Wong, "Performance evaluation of classification algorithms by k-fold and leave-one-out cross validation," *Pattern Recognition*, vol. 48, no. 9, pp. 2839-2846, 2015, doi: 10.1016/j.patcog.2015.03.009.

[26] N. Ahmad and V. Nath, "Evaluating Nine Machine Learning Algorithms for GaN HEMT Small Signal Behavioral Modeling through K-fold Cross-Validation," Engineering, Technology & Applied Science Research, vol. 14, no. 4, pp. 15784–15790, Aug. 2024, doi: 10.48084/ETASR.7726.

[27] T. Fontanari, T. C. Fróes, and M. Recamonde-Mendoza, "Cross-validation Strategies for Balanced and Imbalanced Datasets," Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 13653 LNAI, pp. 626–640, 2022, doi: 10.1007/978-3-031-21686-2_43/TABLES/4.

[28] Kromer-Edwards, M. Castanheira and S. Oliveira, "Using Feature Selection from XGBoost to Predict MIC Values with Neural Networks," 2023 International Joint Conference on Neural Networks (IJCNN), Gold Coast, Australia, 2023, pp. 1-8, doi: 10.1109/IJCNN54540.2023.10191713.

[29] Poornima, R., Elangovan, Mohanraj, and Nagarajan, G. 'Network Attack Classification Using LSTM with XGBoost Feature Selection'. 1 Jan. 2022 : 971 – 984.

[30] U. Vanichrujee, T. Horanont, W. Pattara-atikom, T. Theeramunkong, and T. Shinozaki, "Taxi Demand Prediction using Ensemble Model Based on RNNs and XGBOOST," in Proc. 2018 Int. Conf. Embedded Syst. Intell. Technol. & Int. Conf. Inf. Commun. Technol. Embedded Syst. (ICESIT-ICICTES), Khon Kaen, Thailand, 2018, pp. 1-6, doi: 10.1109/ICESIT-ICICTES.2018.8442063.

[31] Q. Mao, F. Hu and Q. Hao, "Deep Learning for Intelligent Wireless Networks: A Comprehensive Survey," in *IEEE Communications Surveys & Tutorials*, vol. 20, no. 4, pp. 2595-2621, Fourth quarter 2018, doi: 10.1109/COMST.2018.2846401

[32] Pang, B., Nijkamp, E., & Wu, Y. N. (2020). Deep Learning With TensorFlow: A Review. Journal of Educational and Behavioral Statistics, 45(2), 227-248. doi.org/10.3102/1076998619872761

[33] "Regression: An Explanation of Regression Metrics And What Can Go Wrong | by Divyanshu Mishra | Towards Data Science." Accessed: Oct. 11, 2024. [Online]. Available: https://towardsdatascience.com/regression-an-explanation-of-regression-metrics-and-what-can-go-wrong-a39a9793d914

[34] J. Bergstra and Y. Bengio, "Random search for hyper-parameter optimization," *J. Mach. Learn. Res.*, vol. 13, pp. 281-305, 2012. doi: 10.5555/2503308.2188395.

[35] J. Goldhirsh, "Attenuation and backscatter from a derived two-dimensional duststorm model," IEEE Trans Antennas Propag, vol. 49, no. 12, pp. 1703–1711, Dec. 2001, doi: 10.1109/8.982449.

[36] Z. E. O. Elshaikh, M. R. Islam, O. O. Khalifa, and H. E. Abd-El-Raouf, ''Mathematical model for the prediction of microwave signal attenuation due to duststorm,'' Prog. Electromagn. Res. M, vol. 6, pp. 139–153, 2009.

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