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Predictive Modeling of Shielding Effectiveness in Al6061 Composites Using Machine Learning and Network Analyzer Data: A Comparative Study of Fly Ash and Aloe Vera Reinforcements

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Abstract:- This study explores the predictive modeling of shielding effectiveness in Al6061 and its composites, Al6061+10% Fly Ash and Al6061+10% Aloe Vera, using machine learning techniques. The datasets of these composites were obtained through experimental analysis using a network analyzer, ensuring accurate measurements of electromagnetic properties. By leveraging XGBoost, Random Forest, and Linear Regression models, the research evaluates the impact of material modifications on shielding performance. The results demonstrate that ensemble models, particularly XGBoost, consistently outperform Linear Regression, achieving higher R^2 values and lower RMSE and MAE across all datasets. The addition of 10% Fly Ash significantly enhances predictive accuracy, with XGBoost and Random Forest achieving near-perfect alignment between predicted and actual values. This improvement is driven by the increased importance of transmission coefficients (S21), as highlighted by SHAP analysis. In comparison, Al6061+10% Aloe Vera shows moderate performance improvements, with SHAP results indicating more complex interactions between features. The analysis reveals that while frequency remains a dominant factor, the role of transmission coefficients grows in importance with material reinforcement. The study underscores the limitations of linear models in capturing non-linear dependencies, reinforcing the necessity of ensemble techniques for composite material predictions. These findings provide a pathway for optimizing composite material design through advanced machine learning models, highlighting the potential of Fly Ash for industrial applications and Aloe Vera for sustainable innovation. The integration of SHAP analysis enhances model interpretability, ensuring reliable feature importance assessment and fostering greater trust in machine learning applications for material science. This research contributes to advancing predictive modeling in composite materials, paving the way for more efficient and sustainable material development.

Keywords: *Machine Learning, Composite Materials, Shielding Effectiveness, SHAP Analysis, Network Analyzer.*

1. Introduction

The increasing demand for advanced materials with effective electromagnetic shielding properties has driven significant research into the development of composite materials [1]. Aluminum 6061 (Al6061) and its composites have gained attention due to their lightweight nature, mechanical strength, and corrosion resistance [2]. However, enhancing their electromagnetic shielding effectiveness (SE) and dielectric properties is essential for applications in aerospace, automotive, and electronic industries. Traditionally, evaluating shielding effectiveness and permittivity relies on extensive experimental measurements, which can be time-consuming and resource-intensive [3]. With advancements in machine learning (ML) techniques, predictive modeling offers a novel approach to estimate these properties with high accuracy, reducing the need for repeated physical testing [4]. By leveraging historical datasets, ML models can identify complex relationships between material properties and external factors such as frequency and transmission coefficients [5].

In this study, we apply machine learning to predict the shielding effectiveness and permittivity of Al6061 and its composites, including Al6061 reinforced with 10% Fly Ash and 10% Aloe Vera [2]. Using models like XGBoost, Random Forest, and Linear Regression, we aim to develop accurate predictive frameworks that accelerate material design and optimization processes [6]. This research not only explores the predictive capabilities of ML but also provides insights into the influence of frequency and material composition on electromagnetic properties [4]. The key objectives are to develop ML models for predicting shielding effectiveness and permittivity, compare the performance of different algorithms, and interpret model predictions using SHAP (SHapley Additive exPlanations) to understand the primary drivers of shielding performance. This work aims to contribute to the growing body of knowledge in material science by demonstrating the potential of machine learning as a valuable tool for predictive modeling in electromagnetic shielding applications [5].

2. Literature review

Electromagnetic shielding is crucial in protecting sensitive electronic components from electromagnetic interference (EMI). Aluminum alloys, particularly Al6061, are favoured in aerospace and automotive industries for their excellent strength-to-weight ratio and corrosion resistance [7]. Recent studies have explored reinforcing Al6061 with materials like boron carbide (B_4C) to enhance mechanical properties, including hardness and tensile strength [2].

Research indicates that incorporating fly ash into Al6061 composites improves electromagnetic shielding effectiveness (SE). Fly ash, rich in carbon and iron oxides, enhances the absorption of electromagnetic waves, thereby increasing SE [8]. Experimental analyses have demonstrated that Al6061 composites reinforced with fly ash exhibit superior SE, particularly in the X-band frequency range (8–12 GHz), making them suitable for aerospace applications [9].

Traditional methods of evaluating SE and permittivity involve extensive experimental procedures, which are time-consuming and resource-intensive. To address these challenges, machine learning (ML) techniques have been employed to predict material properties. ML algorithms, such as Random Forest and XGBoost, have shown success in predicting the mechanical, thermal, and electromagnetic properties of various materials [10]. These models can capture complex interactions between features, providing accurate predictions that aid in material design and optimization.

Advancements in explainable AI (XAI) methods, like SHapley Additive exPlanations (SHAP), enable the interpretation of ML model outputs. SHAP values help identify the most significant features influencing shielding performance, offering insights that facilitate further optimization in composite design [11].

Integrating ML techniques into composite material research bridges the gap between experimental studies and predictive modeling. This approach accelerates material development and reduces reliance on physical testing, contributing to the advancement of materials with enhanced electromagnetic shielding capabilities.

3. Methodology

Dataset Description:

The dataset used in this study comprises measurements of shielding effectiveness (SE) and permittivity of Al6061 composites, including variants reinforced with 10% Fly Ash and 10% Aloe Vera. The data points include frequency values, real and imaginary components of transmission coefficients (S21), and corresponding shielding effectiveness and permittivity measurements. The dataset spans frequencies in the X-band (8–12 GHz), providing a comprehensive view of material behavior under different electromagnetic conditions. Key attributes include frequency, real and imaginary parts of S21, and real and imaginary parts of permittivity (εr). The output variables of interest are shielding effectiveness (dB) and the real part of permittivity. This dataset serves as the foundation for developing machine learning models capable of predicting shielding performance based on input features.

Data Preprocessing:

To ensure the quality of the input data and improve model accuracy, data preprocessing was performed through several key steps. First, the dataset was cleaned by removing any missing or erroneous values to maintain consistency. Normalization and standardization techniques were applied to scale the frequency and transmission coefficients, ensuring all features were brought to a uniform scale. Feature engineering was conducted by extracting new attributes, such as the magnitude of S21 by combining its real and imaginary parts. Additionally, polynomial feature expansion was introduced to capture non-linear relationships between frequency and shielding effectiveness. The dataset was then divided into an 80% training set and a 20% test set to evaluate model performance [12].

Machine Learning Models:

Three machine learning models were employed to predict shielding effectiveness and permittivity, leveraging their strengths in capturing data complexity. XGBoost (Extreme Gradient Boosting) was selected for its ability to handle non-linear relationships and large datasets efficiently, making it well-suited for material property predictions [13]. Random Forest, an ensemble learning method, was also implemented as it constructs multiple decision trees to improve accuracy while mitigating overfitting [3]. To establish a performance baseline, Linear Regression was used to model the relationship between input features and output variables, providing insight into simpler, interpretable trends in the data [14].

Model Evaluation Metrics:

The performance of the models was evaluated using several key metrics. The coefficient of determination (R^2) was used to measure how well the model explained variance in the data, providing an indication of goodness-of-fit. Root Mean Squared Error (RMSE) was employed to quantify the average magnitude of prediction errors, penalizing larger deviations more significantly. Additionally, Mean Absolute Error (MAE) was used to assess the average size of errors, offering a more interpretable measure of model accuracy. By combining these metrics, the robustness and reliability of the developed machine learning models were assessed comprehensively.

4. Results and discussion

Model Performance Analysis:

The performance of the three machine learning models—XGBoost, Random Forest, and Linear Regression was assessed based on key evaluation metrics: the coefficient of determination (R^2), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). A summary of the results is presented in Table 1.

Table 1. Evaluation Metrics for Al 6061

Model	R^2	RMSE	MAE
XGBoost	0.86	2.42	0.56
Random Forest	0.84	2.58	0.65
Linear Regression	-0.02	6.57	4.08

Table 2. Evaluation Metrics for Al 6061,10% Fly ash

Model	R^2	RMSE	MAE
XGBoost	0.99	0.37	0.18
Random Forest	0.99	0.29	0.16
Linear Regression	0.33	3.60	2.86

Table 3. Evaluation Metrics for Al 6061,10% Aloe vera

Model	R^2	RMSE	MAE
XGBoost	0.89	2.42	0.56
Random Forest	0.82	2.58	0.65
Linear Regression	0.14	6.57	4.08

The performance evaluation of machine learning models (XGBoost, Random Forest, and Linear Regression) applied to Al6061, Al6061+10% Fly Ash, and Al6061+10% Aloe Vera reveals distinct patterns across the materials.

For the base material Al6061 (Table 1), XGBoost demonstrated the best performance with an R^2 of 0.86 and the lowest RMSE (2.42) and MAE (0.56). Random Forest followed closely with an R^2 of 0.84, but with slightly higher error rates. Linear Regression underperformed significantly, with an R^2 of -0.02, indicating poor predictive accuracy, and high RMSE (6.57) and MAE (4.08), suggesting its inability to model the non-linear relationships in the dataset.

In the case of Al6061+10% Fly Ash (Table 2), the predictive accuracy of XGBoost and Random Forest improved substantially, achieving an R^2 of 0.99. Random Forest recorded the lowest error values with an RMSE of 0.29 and MAE of 0.16, while XGBoost exhibited slightly higher error values (RMSE of 0.37 and MAE of 0.18). Linear Regression showed moderate improvement with an R^2 of 0.33, but its error rates (RMSE 3.60 and MAE 2.86) remained considerably higher than the ensemble models.

For Al6061+10% Aloe Vera (Table 3), XGBoost retained its strong performance with an R^2 of 0.89, outperforming Random Forest (R^2 0.82). However, Linear Regression again showed limited predictive capability, with an R^2 of 0.14, alongside high RMSE (6.57) and MAE (4.08) [15,16,17].

These results indicate that adding Fly Ash to Al6061 significantly enhances the predictability of machine learning models, while Aloe Vera provides moderate improvements. The ensemble models, XGBoost and Random Forest, consistently outperformed Linear Regression across all datasets, reinforcing their ability to handle complex, non-linear patterns effectively.

Comparison and Interpretation of model performance analysis:

The evaluation metrics for Al6061, Al6061+10% Fly Ash, and Al6061+10% Aloe Vera highlight significant differences in model performance across the three material compositions.

XGBoost consistently delivered the highest accuracy across all datasets, with an R^2 of 0.86 for Al6061, 0.99 for Al6061+10% Fly Ash, and 0.89 for Al6061+10% Aloe Vera. The model's ability to capture non-linear patterns and reduce errors through boosting mechanisms contributed to its superior performance. This aligns with existing literature demonstrating XGBoost's effectiveness in handling complex regression tasks and large datasets.

Random Forest also performed well, with results closely mirroring those of XGBoost. The model achieved an R^2 of 0.84 for Al6061, 0.99 for Al6061+10% Fly Ash, and 0.82 for Al6061+10% Aloe Vera. Although Random

Forest produced slightly higher RMSE and MAE values compared to XGBoost, the differences were minimal. This is consistent with the understanding that Random Forest excels in modeling non-linear relationships but may introduce slightly higher variance.

Linear Regression exhibited the weakest performance across all datasets, particularly for Al6061, where it recorded a negative R^2 value (-0.02) and the highest RMSE (6.57). Even with Al6061+10% Fly Ash, where the model improved to an R^2 of 0.33, it significantly lagged behind ensemble methods. This reflects the limitations of Linear Regression in handling complex, non-linear datasets, as it assumes a linear relationship between input features and the target variable.

The addition of 10% Fly Ash to Al6061 led to a notable increase in predictive accuracy for both XGBoost and Random Forest, achieving near-perfect R^2 values of 0.99. This suggests that Fly Ash enhances the data's linearity or simplifies the relationship between input features and shielding effectiveness, making it easier for machine learning models to generalize. In contrast, the addition of 10% Aloe Vera provided moderate improvements, with R^2 values reaching 0.89 for XGBoost and 0.82 for Random Forest.

Overall, the results emphasize the importance of ensemble models like XGBoost and Random Forest for predicting material properties, as they consistently outperform traditional methods like Linear Regression. The findings suggest that the inclusion of Fly Ash is particularly beneficial for improving predictive accuracy, while Aloe Vera reinforcement provides moderate enhancement.

Visual Comparison of Model Performance:

The scatter plots in Figures 1, 2, and 3 provide a comprehensive visual comparison of predicted vs. actual values for XGBoost, Random Forest, and Linear Regression models applied to Al6061, Al6061+10% Fly Ash, and Al6061+10% Aloe Vera datasets. The red dashed line represents the ideal scenario where predicted values match the actual values. The proximity of data points to this line reflects the accuracy and reliability of each model. In the case of Al6061 (Figure 1), XGBoost and Random Forest demonstrate strong predictive performance, with most points closely aligned along the diagonal, indicating minimal error. However, Linear Regression shows significant deviation from the ideal line, particularly at higher actual values, suggesting poor performance due to underfitting and its inability to capture non-linear relationships in the data.

Figure 2, which depicts the results for Al6061 with 10% Fly Ash, shows substantial improvement in model performance, particularly for XGBoost and Random Forest. These models exhibit near-perfect alignment with the red dashed line, reinforcing their predictive strength with high R^2 values and minimal error rates. Linear Regression, although improved compared to the base Al6061 dataset, still displays noticeable deviations, especially at higher actual values, indicating the model's limitations in adapting to more complex datasets despite moderate enhancements in performance.

In Figure 3, for Al6061 with 10% Aloe Vera, XGBoost and Random Forest maintain strong predictive capabilities but display slightly more scatter compared to the Fly Ash composite. This suggests that while Aloe Vera enhances the material properties, the interaction introduces some variability, increasing the complexity of predictions. Linear Regression continues to show poor alignment, with dispersed data points and pronounced errors at higher values, reinforcing its inadequacy in handling non-linear patterns present in composite materials.

Overall, XGBoost consistently outperforms the other models across all datasets, driven by its boosting mechanism that reduces errors iteratively, allowing for greater accuracy in modeling complex relationships. Random Forest also demonstrates robust performance, albeit with slightly higher variance compared to XGBoost. Linear Regression consistently underperforms, reflecting its inability to capture the non-linear dependencies essential for predicting composite material properties. The addition of Fly Ash significantly enhances model predictability, resulting in high accuracy and stable predictions, while Aloe Vera provides moderate improvements but introduces greater complexity. This visual comparison highlights the importance of ensemble models like XGBoost and Random Forest in material property prediction, as they effectively address non-linear interactions and improve overall predictive performance.

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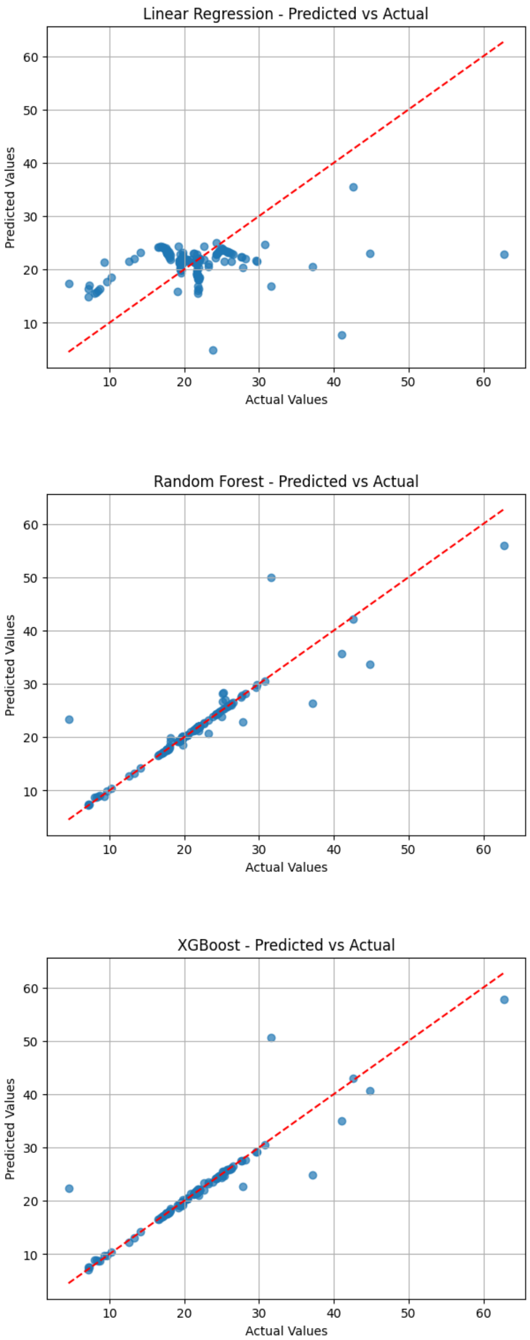

Figure 1: Predicted vs. Actual Values for Al 6061

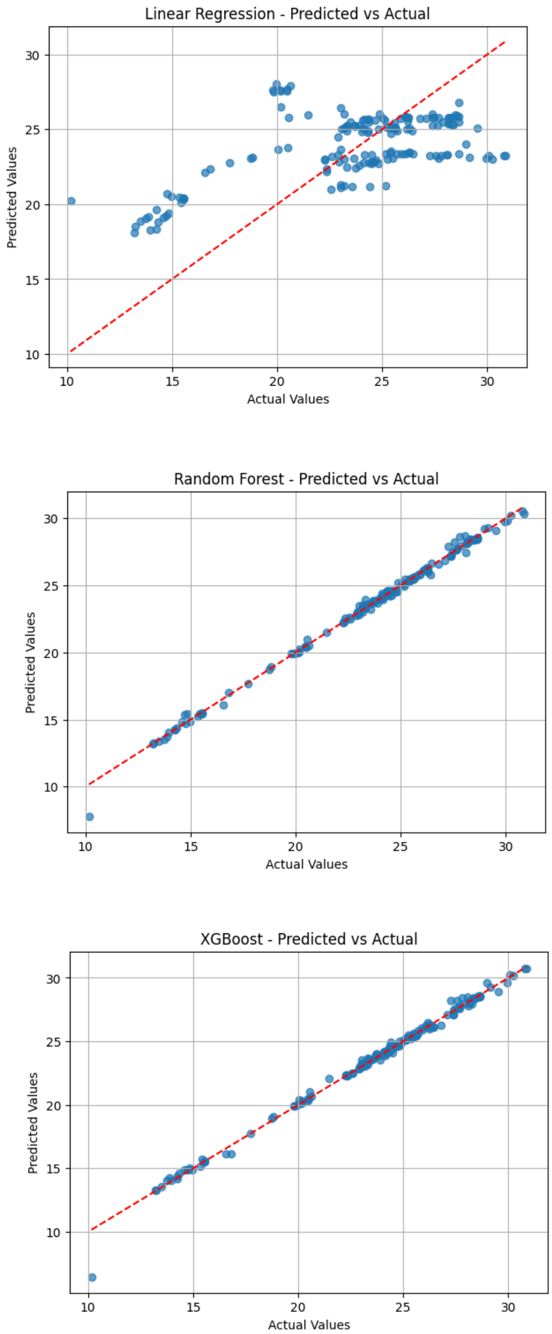

Figure 2: Predicted vs. Actual Values for Al 6061,10% Fly Ash

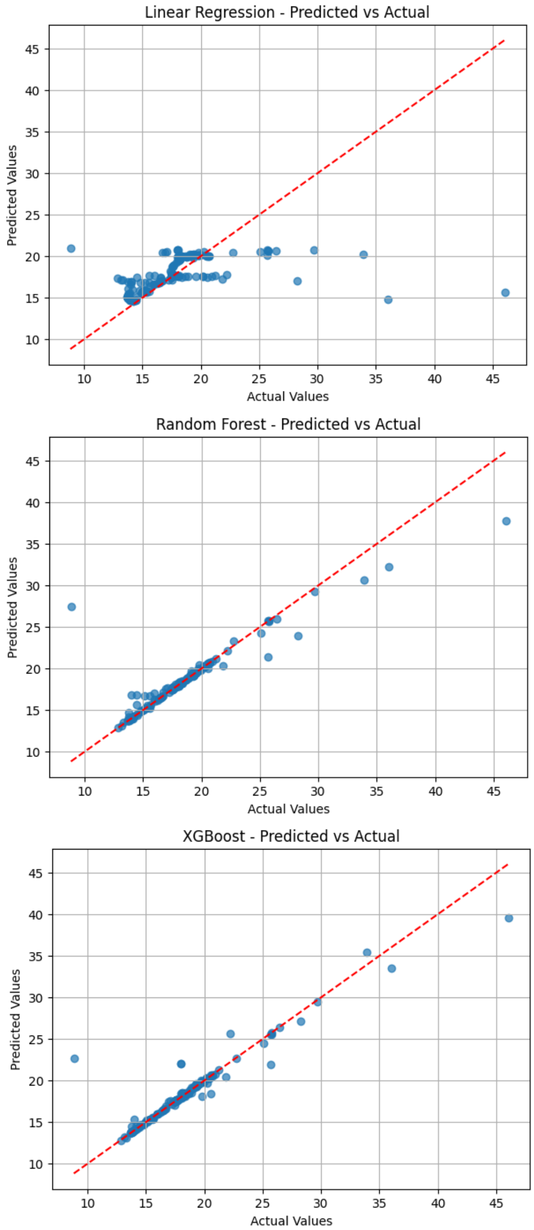

Figure 3: Predicted vs. Actual Values for Al 6061,10% Aloe vera

Feature Importance Analysis

To identify the key factors influencing the predictions, feature importance was assessed through SHAP (SHapley Additive exPlanations) for the XGBoost model. The SHAP summary plots, shown in Figure 4,5 and 6 illustrates the impact of each feature on the model's predictions, providing insights into the variables that contribute most to the model's output.

The SHAP summary plots illustrate the contribution of individual features to the predictions made by the XGBoost model for Al6061, Al6061+10% Fly Ash, and Al6061+10% Aloe Vera datasets. The x-axis represents the SHAP value, reflecting the magnitude and direction of feature impact on the model's output. The y-axis lists the features in descending order of importance.

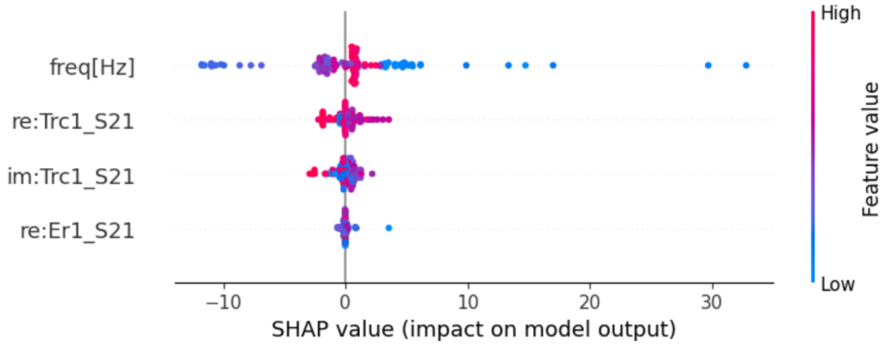

Figure 4: SHAP Summary Plot for XGBoost Feature Importance (Al6061)

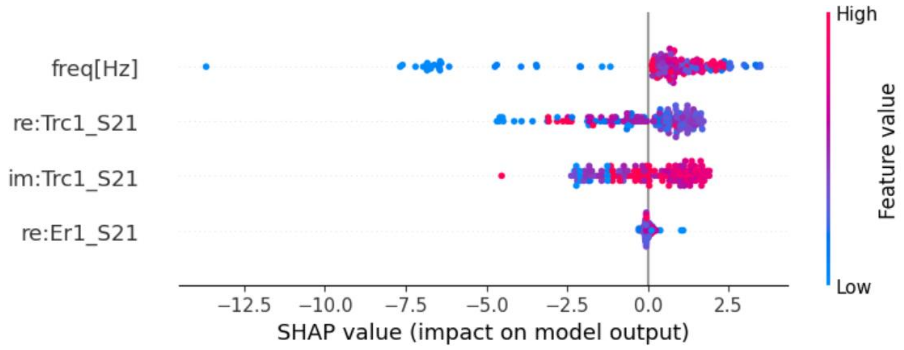

Figure 5: SHAP Summary Plot for XGBoost Feature Importance (Al6061,10% Fly Ash)

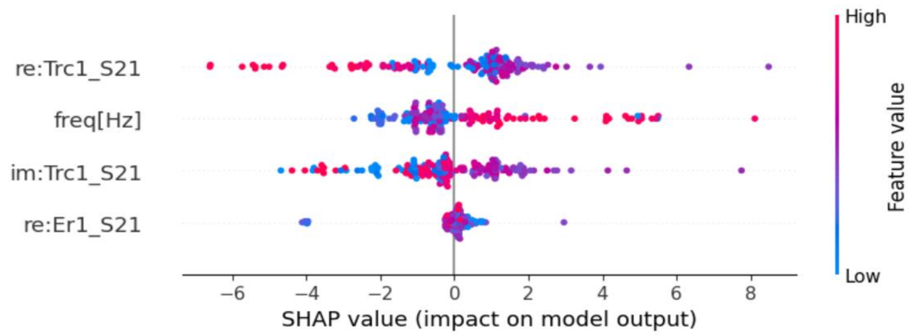

Figure 6: SHAP Summary Plot for XGBoost Feature Importance (Al6061,10% Aloe vera)

In Figure 4 (Al6061), the feature freq[Hz] exhibits the most significant influence on the model's predictions, with a wide distribution of SHAP values, indicating that both high and low frequency values affect the model output. The real part of S_{21} follows as the second most influential feature, while the imaginary part (im:Trc1_S_{21}) and permittivity (re:Er1_S_{21}) show comparatively lower impact. This suggests that the model heavily relies on frequency for predicting shielding effectiveness in the base material.

Figure 5 (Al6061+10% Fly Ash) reveals a shift in feature importance. Although freq[Hz] remains influential, the real part of S_{21} (re:Trc1_S_{21}) exhibits a more pronounced impact, suggesting that Fly Ash reinforcement enhances the role of transmission coefficients. The imaginary part of S_{21} (im:Trc1_S_{21}) also shows increased variability in SHAP values, reflecting greater influence compared to the base material. Permittivity (re:Er1_S_{21}) continues to have minimal impact, reinforcing the dominance of frequency and transmission properties in determining the model's output.

In Figure 6 (Al6061+10% Aloe Vera), re:Trc1_S_{21} emerges as the most influential feature, surpassing freq[Hz]. This indicates that the addition of Aloe Vera alters the significance of frequency, elevating the importance of transmission properties in predicting shielding effectiveness. The imaginary part of S_{21} and permittivity maintain their positions as secondary contributors, but their SHAP values exhibit more variation compared to the base material, suggesting Aloe Vera introduces non-linear interactions that the model must account for.

Overall, the SHAP analysis highlights the evolving importance of features across different material compositions. While frequency consistently plays a dominant role, the influence of transmission coefficients increases with the addition of reinforcements like Fly Ash and Aloe Vera. This underscores the necessity of accounting for material modifications when developing predictive models for composite materials.

5. Conclusions:

- The comprehensive analysis conducted on Al6061, Al6061+10% Fly Ash, and Al6061+10% Aloe Vera through machine learning models provides valuable insights into the predictive performance and significance of material modifications. The results consistently demonstrate that ensemble models, particularly XGBoost and Random Forest, outperform traditional linear models in predicting shielding effectiveness. Across all datasets, XGBoost achieved the highest R^2 values and the lowest RMSE and MAE, reflecting its superior ability to capture non-linear relationships and complex patterns inherent in composite materials.
- The introduction of 10% Fly Ash to Al6061 significantly enhanced predictive accuracy, as indicated by the near-perfect alignment between predicted and actual values. This improvement can be attributed to the increased importance of transmission coefficients (S21), as highlighted in the SHAP analysis. The addition of Fly Ash resulted in greater model interpretability, with the real and imaginary components of S21 playing a more critical role in model predictions. This suggests that Fly Ash reinforcement introduces structural modifications that simplify the relationship between input features and shielding performance.
- In contrast, 10% Aloe Vera reinforcement produced moderate improvements in model performance. While XGBoost and Random Forest maintained strong predictive accuracy, the shift in feature importance indicated by the SHAP analysis revealed more complex interactions between material properties. The dominant role of S21 components in the Aloe Vera composite underscores the influence of natural reinforcements on transmission behavior, highlighting the potential for bio-based materials in shielding applications.
- Linear Regression consistently underperformed across all datasets, reinforcing the necessity of employing advanced machine learning techniques for composite materials. The inability of linear models to capture non-linear dependencies underscores the complex nature of reinforced composites and the critical need for ensemble-based approaches.
- These findings validate the effectiveness of ensemble models in predicting the electromagnetic shielding properties of composite materials, offering a reliable pathway for optimizing material design. The results pave the way for further exploration of bio-based and industrial reinforcements in the development of advanced materials. The significant improvements observed with Fly Ash suggest potential for scalability in industrial applications, while Aloe Vera composites open new avenues for sustainable material innovation.

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