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REGULAR ARTICLE

Forecasting Dielectric Behavior of Nano-Epoxy Materials through AI-based Electronic Properties

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To predict the dielectric behavior of nano-epoxy composites, sophisticated machine learning algorithms were suggested. Dielectric characteristics were precisely estimated to maximize the use of the nano-epoxy composite in electronics. Using AI models and data on their electrical properties, the objective is to predict the dielectric behavior of nano-epoxy materials. To achieve consistent feature contributions, the dataset was preprocessed using min-max normalization, which normalized the range of input characteristics. Therefore, present the Fine-tuned Squirrel Search Algorithm-driven Malleable AdaBoost model (FSS-MAdaBoost), which combines MAdaBoost with the FSS. This hybrid model may overcome the typical drawbacks of improved prediction accuracy and the successful handling of complicated and nonlinear connections between features. The suggested model is compared to an existing model. The performance was evaluated using RMSE (0.018) and MAE (0.01) measures. According to the foregoing results, the FSS-MAdaBoost-based model outperforms previous approaches with much lower values of RMSE and MAE, indicating superior predictions and dependability. The results indicated promising directions for dielectric property forecasting using the FSS-MAdaBoost model for nano-epoxy materials, providing valuable insights that material scientists and engineers can use to optimize material design, thereby improving electronic applications.

Keywords: Dielectric behavior, Nano-epoxy materials, Artificial intelligence, Machine learning models, FSS-MAdaBoost.

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1. INTRODUCTION

The increased mechanical and electrical features of nanoscale reinforcement in epoxy resin were the focal point of interest among diverse fields of application, starting from electronics and electrical insulation. Such properties of the material comprise dielectric behavior-permittivity, dielectric strength, and loss tangent [1]. Thus, in the context of electric insulation-related applications, energy storage, and high-voltage ambiance, the above-mentioned properties represent materials' performance and reliability. Nano-epoxy materials have complex dielectric characteristics, as the relationship between epoxy matrix and nanofillers engaged is highly sensitive to many parameters such as nanoparticle size, concentration, and dispersion [2]. The overwhelming requirements of experimental testing make classical methods for calculating dielectric characteristics consume much more time and money. One interesting method of dielectric behavior forecast in terms of material electrical characteristics was artificial intelligence (AI) [3]. With such a dataset, AI may find patterns and connections amid dielectric responses for nano-epoxy compositions. It gives insight into how to develop and improve nano-epoxy materials to be used in high-performance applications for advanced electronics, helps predict the material's efficiency, and reduces the need for lengthy testing [4]. The epoxy resin material had dielectric properties significantly improved due to nanoscale particles and, thus, considerably increased its prospects for use in modern electrical and electronic devices. Low dielectric loss, and specific characteristics of the many types of nano-epoxy materials are particularly relevant to microelectronic devices, high-voltage insulators, and power storage technologies [5-6]. Due to the complexity, a single conventional experimental approach fails to completely capture the underlying

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relationships that form the basis of dielectric behavior; hence, it is more restricted by cost and time factors [7]. Artificial intelligence has been standard as an effective solution to model complex relationships in material science in recent years. AI, through machine learning and deep learning techniques, predicts the electronic properties-based dielectric behavior of nano-epoxy composites, thus providing a very promising tool against conventional testing limitations [8].

2. RELATED WORK

The effects of artificial nanoparticles on undoped epoxy composites were examined, with a focus on their potential use in dielectric materials. Nano epoxy composites were usually synthesized and characterized experimentally using costly and time-consuming techniques. To address the difficulty, evaluate the machine learning (ML) models, gradient boosting, XGBoost, decision trees, random forests, and additional trees. Those models were used to forecast the frequency-dependent dielectric coefficients in these composite over various nanofiller changes [9].

Combining 3D-connected AF with Al_2O_3 microparticles results in a high heat conductivity and significant increase [10]. The composites possible for temperature transmission submissions in microelectronics was suggested by its reduced CTE when compared to the majority of epoxy-based composites.

The fabrication offe_3O_4 , $Nife_2O_4$ and $Cofe_2O_4$ nanoparticles as well as their nanoparticle-doped epoxy composites were examined [11]. Several methods were used to examine the nano-composites structural, optical, and dielectric characteristics. The superficial morphology was inspected using field emission electron microscopy (FESEM), and the occurrence of several compounds was confirmed using electron deflection spectroscopy (EDS). The chemistry and surface functioning were examined using Fourier transform infrared spectroscopy (FTIR), though the structural features remained ascertained using XRD.

The microwave dielectric reduction spectroscopy of epoxy resin composites doped with TiO_2 + ZnO and bisphenol-A resin. The structural properties were found using X-ray diffraction and ultrasonic dispersion methods [12]. The results bring new insights into the structural characteristics and polarization processes of those composite substances.

3. METHODOLOGY

The method uses a preprocessed dataset for nano-epoxy materials and the properties of normalization, including min-max normalization for consistency. A technique dubbed FSS-MAdaBoost has been presented, which combines the FSS-MAdaBoost in the hopes of increasing prediction accuracy. The application in error metrics using RMSE and MAE is less than any previously acquired approach, indicating that it accurately edicts dielectric characteristics for material optimization applications.

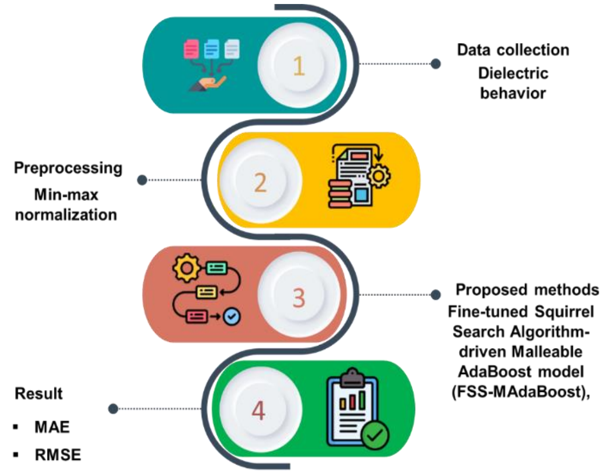

Fig. 1 – Overall flow of the research

3.1 Data Collection

The collection includes a variety of nano-epoxy material parameters. The characteristics of various epoxy resin types, nanoparticles, and their concentrations are to show how they affect dielectric behavior. Various samples with properties that vary, including the type of epoxy resin, the types and concentrations of nanoparticles, conductivity, permittivity, polarizability, curing temperature, the dielectric constant, and the loss tangent. This is also essential in predicting how nano-epoxy materials would behave as dielectrics. With such information, it is then possible to predict the optimization required for these nano-epoxy materials for such cutting-edge applications by considering the link established between the kind and concentration of nanoparticles and their total electrical characteristics.

3.2 Data Pre-processing Using Min-Max Normalization

For predicting the dielectric behavior of nano-epoxy materials using AI-based electronic property analysis, Min-Max normalization is used as a data preparation approach. Signal levels are balanced between 0 and 1, eliminating uneven distribution or inconsistency in data. As a result, this normalization produces improved results in dielectric property forecasts for dependable electronic applications utilizing nano-epoxy materials. The initial data is transformed linearly using min-max normalization. Normalization of values occurs within the designated range. To translate *the* u value of an attribute B from $[min_B, max_B]$ to$[new_{min_B}, new_{max_B}]$, use the following equation (1):

$$u' = \frac{u - min_B}{max_B - min_B}(new_{min_B}, new_{max_B}) + new_{min_B} \quad (1)$$

Where u' represents the new value in the specified range. Min-Max normalization ensures all values fall inside a specific range.

3.3 Fine-tuned Squirrel Search Algorithm-driven Malleable AdaBoost model (FSS-MAdaBoost)

To present a hybrid model Fine-tuned Squirrel Search Algorithm-driven Malleable AdaBoost (FSS-MAdaBoost), which improves the predicted accuracy of dielectric behavior in nano-epoxy materials. The FSS-MAdaBoost model combines MAdaBoost with the FSS, enabling for fine-tuning of model parameters and adaptation to complicated, non-linear correlations in the data. The hybrid technique meets the goal by resolving the constraints of conventional machine learning approaches, resulting in an adaptable and resilient solution that greatly decreases prediction errors. The suggested FSS-MAdaBoost improves performance by precisely capturing the dielectric characteristics required for use in material science and electronics.

3.3.1 Malleable AdaBoost

The malleable AdaBoost is utilized here to improve the flexibility and accuracy of dielectric behavior prediction of nano-epoxy material. Dynamic optimization is achieved by modifying AdaBoost's fitting model such that it captures minor electrical features with great accuracy to dependable dielectric predictions. Adaptive boost is an iterative technique that creates a single strong classifier by combining many weak classifiers. This algorithm's main concept is to train several feeble classifiers for the same and the term in equation (3) is bigger than that in equation (2) since $g_{s-1}(w_j)$is greater than 0. It is a major error to misclassify samples that have already been appropriately categorized. Therefore, the next classifier should pay more attention to these data and assign this example a greater weight. The weight adjustment technique might help the subsequent weak classifier pay more attention to samples that are changed from positive to negative by the present built classifier, lowering the likelihood that they would be incorrectly categorized.

$$C_{s+1}(j) = \frac{C_s(j)\exp\left(-\alpha_s, z_j g_s(w_j)\right)}{Sum\ (C)} \quad (2)$$

$$C_{s+1}(j) = \frac{C_s(s)\exp\left(-\alpha_s z_j g_s(w_j) + \beta z_j E_{s-1}(w_j) g_{s-1}(w_j)\right)}{sum(C)} \quad (3)$$

$$C_{s+1}(j) = \frac{C_s(j)\left(f^{-\alpha_s, z_j g_s(w_j)}\right)^{\frac{1-err}{l-\eta}}}{sum(C)} \quad (4)$$

If a section is misclassified more than once, equation (4) will be utilized as the weight updating equation instead of equation (2). The threshold of inaccuracy counts, or err, is the error rate of the previous round classifier on the model set; in other words, the penalty term takes effect when the counts of persistent misclassifications of a model surpass the threshold. In equation (2), $f^{-\alpha_s, z_j g_s(w_j)}$is greater than 1 and $1-\alpha_s, z_j g_s(w_j)$is in the range (0, 1), and $z_j g_s(w_j) < 0$. Thus, $\left(f^{-\alpha_s, z_j g_s(w_j)}\right)^{\frac{1-err}{l-\eta}}$ is more than $\frac{1-err}{l-\eta}$.

The enhanced method gives greater consideration to the classifier's error rate and the frequency of incorrect classifications in the second instance. This updated technique of enhanced weight suppresses weight distortion and decreases the expanding variety of model mass identified by the earlier round of feeble classifiers. The classifier trained in the prior curve properly categorized the sample; however, in this round it classified it wrongly. The samples were erroneously categorized in both this round and the prior round by the classifier that was trained.

Let z_j represent the correct classification of apiece model j, $g_{s-1}(w_j)$ represent the earlier classification outcome, $g_s(w_j)$ represents the outcome in this round, ft (xi) represents the mass of the present classifier, and$E_{s-1}(w_j) + e_s(w_j)$. The test weight update equation for the conventional approach is equation (2). The proponent is bigger than 0 and the model mass is raised if a sample is misclassified, meaning that $z_j g_s(w_j) < 0$. The first instance of misclassification is handled by the enhanced algorithm using equation (3). Since $\beta > 0$ in equation (3), $z_j g_s(w_j)$ is smaller than 0. In other situations, the conventional weight update approach will continue to be applied. With w_j and $z_j$standing for a mark that corresponds to each sample and the position in the sample space, $T = \{(W_1, Z_1), (W_2, Z_2) \dots (W_M, Z_M)\}$. The amount of samples taking part in the training is M.

Set the initial weight of vector C, which represents the mass of the individual sample in the training information. The same weight, 1 over M, is assigned to each sample. For training, the weak learning process $g1$ was employed. Following preparation, the error rate was determined using equation (5). M_{err} is the number of models that were misclassified.

$$\varepsilon = \frac{M_{err}}{M} \quad (5)$$

Determine the weak learning algorithm's weight. Vector α represents the mass of the feeble learner algorithm, which is determined by the mistake amount in equation (6),

$$\alpha = \frac{1}{2} In\left(\frac{1-\varepsilon}{\varepsilon}\right) \quad (6)$$

Each sample weight should be updated. Equation (2) is the weight update calculation in the initial instance of misclassification explored in section. Equation (4) will be used if the second instance of misclassification occurs. After adjusting the sample weight based on each training outcome and the most current total classification's accuracy, this method uses the new data to train the next weak classifier. As the last choice classifier, Adaboost determines the precision of the current poor classifiers and merges them into a malleable classifier. When certain requirements are fulfilled, the iterative process comes to an end. The aforementioned analyses demonstrate that as Adaboost iteration progresses, the weight of mistake samples will rise. This phenomenon seeks to focus the classifier's focus on wrongly classified data. The classifier's overall performance will surely be impacted if this issue is allowed to grow indefinitely. This study pays attention to the mass adjustment techniques of the two categorization situations listed below to mitigate this issue; every weak classifier's weight and output are determined following t-round learning. Equation (7) displays the algorithm's ultimate result.

$$G(W) = sign\left(\sum_{j=1}^{s} \alpha_j g_j(W)\right) \quad (7)$$

4. RESULT

Results were obtained from trials with the Python 3.11 software. The investigation was conducted using a laptop running Windows 10 with an Intel i7 CPU and 32 GB of RAM. The feature significance ratings for the several elements affecting the dielectric behavior of nano-epoxy materials are shown in Fig. 2. The most crucial component of the model is permittivity, which increases prediction accuracy by 0.40. Similarly, the relevance score of characteristics is increased by 0.20, 0.15, and 0.15, respectively, by nanoparticle type, conductivity, and curing temperature. These characteristics are crucial for making precise predictions, therefore they fit in nicely with the study's goal of enhancing dielectric property prediction.

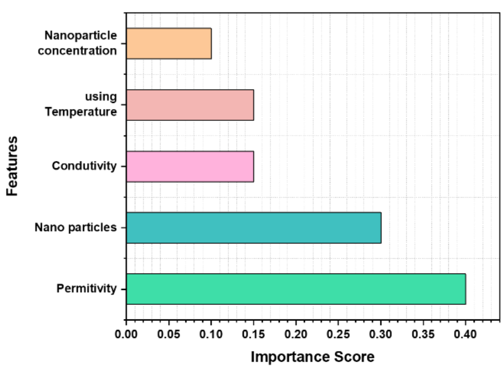

Fig. 2 – Forecasting nano-epoxy material dielectric behavior

A visual comparison between anticipated and actual values is provided by the anticipated vs. Actual Dielectric Constant plot, Fig. 3 which is used to assess how well the model predicts the dielectric behavior of nano-epoxy materials. The model's projected dielectric constants for different nano-epoxy samples are shown by the blue dots, and complete prediction alignment is shown by the red line. High prediction accuracy is shown by points around this line, which directly supports the goal of creating a precise. AI-driven model for dielectric property forecasting. Considerable departures from the line indicate regions where more model improvement may improve prediction accuracy, hence enhancing the model's dependability in real-world scenarios.

Comparison between the proposed method Fine-tuned squirrel search algorithm-driven malleable AdaBoost (FSS-MAdaBoost) with existing methods Random Forest (RF), Decision Tree (DT), and Extra Trees (ET) [13]

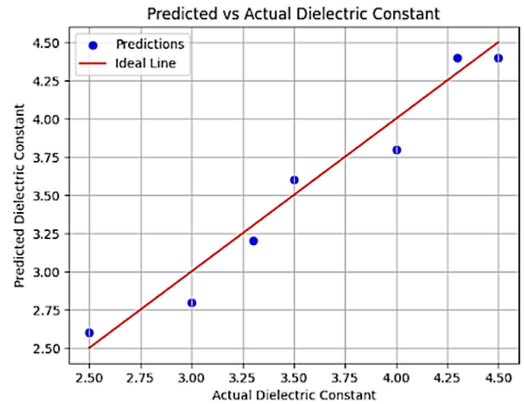

Fig. 3 – Plotting the predicted and actual dielectric constants to assess model performance

Table 1 – Quantitative outcomes of the suggested methods

Method	MAE	RMSE
RF [17]	0.021	0.035
DT [17]	0.023	0.032
ET [17]	0.013	0.022
FSS-MAdaBoost [Proposed]	0.01	0.018

is lower than the proposed method. Compared the existing methods with the MAE, and RMSE parameters. Table 1 shows the Quantitative outcomes of the suggested methods

5. DISCUSSION

Optimizing the use of nano-epoxy materials in electrical applications requires precise prediction of their characteristics, such as their dielectric behavior. Capacitors and insulators may be designed as efficiently as possible using high-precision predictions of these characteristics. To forecast the dielectric characteristics, a few of the current machine-learning techniques, including RF, DT, and ET, were examined. With an RMSE of 0.035 and an MAE of 0.021, the RF model was operating at a respectable but subpar level for the complex nonlinear connections involved in the material characteristics. DT indeed experienced issues with greater errors, particularly with more diversified datasets, with an RMSE of 0.032 and an MAE of 0.023. ET performed better than DT at 0.022 RMSE and 0.013 MAE, as in the previous trial, but it was yet unable to reduce errors to the level necessary for a high-accuracy prediction.

6. CONCLUSION

To obtain a distinct FSS-MAdaBoost model to predict the dielectric behavior of nano-epoxy material accurately, combining the provisions of adaptive boosting along with fine-tuned Squirrel Search. It has also been tested on crucial metrics like MAE and RMSE. Compared to existing prediction-related methods like RF, DT, and ET, the proposed model surfaces as the best fit. FSS-MAdaBoost with the lowest RMSE (0.018) and MAE (0.01) demonstrates the least minimal error minimization compared to the other models. In addition, the RMSE and MAE values of the latter were higher. It displays a failure to predict the dielectric behavior of nano-epoxy material. The precision and robustness of the FSS-MAdaBoost model could be beneficial to rely on accurate predictions in material science and similar fields, which are consistent with the findings of the present work.

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Прогнозування діелектричної поведінки наноепоксидних матеріалів за допомогою електронних властивостей на основі штучного інтелекту

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Для прогнозування діелектричної поведінки наноепоксидних композитів було запропоновано складні алгоритми машинного навчання. Діелектричні характеристики були точно оцінені для максимізації використання наноепоксидного композиту в електроніці. Використовуючи моделі штучного інтелекту та дані про їхні електричні властивості, метою є прогнозування діелектричної поведінки наноепоксидних матеріалів. Для досягнення узгодженого внеску характеристик набір даних був попередньо оброблений за допомогою нормалізації min-max, яка нормалізувала діапазон вхідних характеристик. Тому представлена модель Malleable AdaBoost, керована алгоритмом пошуку білки (FSS-MAdaBoost), яка поєднує MAdaBoost з FSS. Ця гібридна модель може подолати типові недоліки покращеної точності прогнозування та успішної обробки складних та нелінійних зв'язків між характеристиками. Запропонована модель порівнюється з існуючою моделлю. Продуктивність була оцінена за допомогою вимірювань RMSE (0,018) та MAE (0,01). Згідно з вищезазначеними результатами, модель на основі FSS-MAdaBoost перевершує попередні підходи зі значно нижчими значеннями RMSE та MAE, що свідчить про кращі прогнози та надійність. Результати вказали на перспективні напрямки прогнозування діелектричних властивостей за допомогою моделі FSS-MAdaBoost для наноепоксидних матеріалів, надаючи цінну інформацію, яку вчені-матеріалознавці та інженери можуть використовувати для оптимізації дизайну матеріалів, тим самим покращуючи електронні застосування.

Ключові слова: Діелектрична поведінка, Наноепоксидні матеріали, Штучний інтелект, Моделі машинного навчання, FSS-MAdaBoost.