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ORIGINAL STUDY

Development of a Hybrid Intelligence Algorithm to Estimate the Derivative Weight of Dawakin Tofa Clay for Heat Storage

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ABSTRACT

The accurate prediction of thermogravimetric properties is critical for evaluating the suitability of natural materials like Dawakin Tofa clay for heat storage applications, but traditional linear models often fail to capture the complex, non-linear relationships inherent in such datasets. This study develops a hybrid intelligence framework integrating Bilateral Neural Network (BNN), Kernel Support Vector Machine (KSVM), Step-Wise Linear Regression (SWLR), and Robust Linear Regression (RLR) to predict the derivative weight of Dawakin Tofa clay based on 5,030 experimentally obtained instances. Comprehensive data preprocessing, including normalization, feature selection, and dataset splitting (80% training and 20% testing), ensured high-quality inputs for the models. The results demonstrated that non-linear models significantly outperformed linear approaches, with BNN achieving a coefficient of determination R^2 of 0.999, a Mean Absolute Error (MAE) of 0.004377, and a Mean Absolute Percentage Error (MAPE) of 9.6% on the testing dataset. Similarly, KSVM achieved an R^2 of 0.999, MAE of 0.012134, and MAPE of 26.7%, indicating its robust predictive capabilities. In contrast, linear models performed poorly, with SWLR and RLR yielding R^2 values of 0.03 and -0.41, respectively, and unacceptably high MAPE values of 612% and 53.5%. The findings underscore the limitations of linear models in predicting complex thermogravimetric behaviors and highlight the transformative potential of advanced machine learning techniques like BNN and KSVM. Furthermore, these results align with global sustainability efforts, including SDG 7 and 12, by optimizing the use of locally available, eco-friendly materials for energy storage. This study provides a replicable framework for leveraging artificial intelligence to enhance material characterization, offering a significant step toward developing sustainable energy solutions.

Keywords: Dawakin Tofa clay, Thermogravimetric analysis, Machine learning models, Energy storage materials, Sustainable development goals

1. Introduction

The increasing global demand for efficient energy storage systems has driven significant advancements in the development of thermal energy storage (TES) technologies, which play a crucial role in enhancing the sustainability of energy systems, particularly in the context of renewable energy sources [1]. Among the materials explored for TES, clays have gained attention due to their favorable thermal properties, widespread availability, and cost-effectiveness. Dawakin Tofa clay, a naturally abundant clay found in Nigeria, is a promising candidate for heat storage applications [2]. However, optimizing its thermal

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properties, specifically the derivative weight related to heat storage capacity, presents a significant challenge that requires advanced computational approaches. The shift towards renewable energy sources necessitates the development of efficient and reliable energy storage systems to manage the intermittent nature of resources such as solar and wind. TES systems are particularly valuable in this regard, as they can store excess thermal energy generated during peak periods and release it when needed, contributing to grid stability and energy security [3].

Clays, including Dawakin Tofa clay, have been identified as potential materials for TES due to their high heat capacity, thermal conductivity, and stability at elevated temperatures [4]. However, the thermal properties of clays can vary significantly depending on factors such as composition, processing, and environmental conditions. Therefore, accurately estimating the derivative weight, which is closely related to the heat storage capacity, is essential for optimizing the performance of clay-based TES systems [5]. Traditional methods of estimating the derivative weight of materials often rely on experimental measurements and empirical models, which can be time-consuming, resource-intensive, and may not fully capture the complex interactions between different variables. In contrast, hybrid intelligence algorithms provide a more efficient and accurate approach by leveraging AI and ML techniques to analyze large datasets, identify patterns, and make predictions based on complex, non-linear relationships. These algorithms can be trained on experimental data to develop predictive models that estimate the derivative weight of Dawakin Tofa clay under various conditions, providing valuable insights into its thermal behavior and potential for heat storage applications [6].

Hybrid intelligence algorithms, which integrate various computational techniques, including artificial intelligence (AI), machine learning (ML), and traditional optimization methods, have emerged as powerful tools in the field of materials science and engineering. These algorithms have demonstrated great potential in predicting, optimizing, and analyzing complex material properties, thus accelerating the development of advanced materials for various applications [7]. Hybrid intelligence refers to the integration of multiple computational techniques to address complex problems that are beyond the capabilities of individual methods. In the context of materials science, hybrid intelligence algorithms combine AI and ML techniques with traditional optimization methods to enhance the accuracy and efficiency of material property predictions [8]. For instance, machine learning models such as artificial neural networks (ANNs), support vector machines (SVMs), and decision trees can model the relationships between input variables (e.g., clay composition, temperature, pressure) and output variables (e.g., derivative weight, heat capacity). These models can be further refined using optimization techniques such as genetic algorithms (GAs), particle swarm optimization (PSO), and simulated annealing (SA) to improve their predictive accuracy and generalization capabilities [9].

The study develops a ML algorithm to estimate the derivative weight of Dawakin Tofa clay, thereby enhancing its application potential in TES systems. The successful development of a hybrid intelligence algorithm for estimating the derivative weight of Dawakin Tofa clay holds significant potential for various applications. Primarily, it can improve the efficiency and performance of clay-based TES systems by providing accurate predictions of the material's heat storage capacity under varying conditions. This, in turn, can lead to more effective design and optimization of TES systems, facilitating the broader adoption of renewable energy technologies and reducing reliance on fossil fuels. Moreover, the insights derived from the algorithm can inform the selection and treatment of clays for specific TES applications, enabling the development of customized materials with tailored thermal properties. By integrating AI, ML, and optimization techniques, this approach offers a more efficient and accurate method for predicting the thermal properties of clays, thereby enhancing their potential for use in TES systems. The insights gained from this study contribute to the development of more efficient and sustainable energy storage technologies, supporting the transition to a low-carbon economy and addressing the growing demand for renewable energy [10]. Furthermore, the methodology developed in this study has broader applicability in materials science and engineering, making it a valuable contribution to the field of computational materials science. Evolving a hybrid intelligence algorithm to estimate the derivative weight of Dawakin Tofa clay involves several key steps. Initially, relevant data must be gathered through experimental studies or simulations, including measurements of the clay's thermal properties under different conditions. This data forms the foundation for training the machine learning models. Subsequently, feature selection and engineering techniques are employed to identify the most relevant input variables and transform the data into a suitable format for model training [11, 12].

Beyond thermal energy storage, the methodology developed in this study can be extended to other areas of materials science and engineering, where accurate prediction and optimization of material properties are crucial [13]. AI algorithms can be applied to optimize the composition and processing of composite materials, predict the mechanical properties of alloys, or model the behavior of polymers under different environmental conditions. The interdisciplinary nature of this approach, which combines materials science, computational intelligence, and optimization, opens new avenues for research and innovation across a wide range of fields [14]. The research highlighted significant as it advances the understanding and utilization of natural materials for sustainable energy applications. By accurately predicting the derivative weight of Dawakin Tofa clay using a novel hybrid intelligence algorithm, the study provides valuable insights into the material's thermogravimetric behavior, a critical factor for assessing its suitability in heat storage systems. This work supports the development of cost-effective, natural, and eco-friendly energy storage solutions, addressing the global demand for sustainable and renewable energy technologies. The research also holds practical implications for energy storage technologies, where thermal stability and efficiency are paramount. By identifying and optimizing the properties of natural materials like Dawakin Tofa clay, the study aligns with sustainable development goals and supports the transition to green energy systems. Furthermore, the hybrid intelligence algorithm developed in this study has the potential to revolutionize predictive modeling across various domains, extending its applicability beyond heat storage to include other fields such as construction materials, catalysis, and environmental management. Ultimately, this work offers a significant step forward in the integration of AI with material science, contributing to both scientific knowledge and practical solutions for global energy challenges.

This study presents a groundbreaking contribution to the field by introducing a novel hybrid intelligence algorithm that integrates BNN, SWLR, RLR, and KSVM to predict the derivative weight of Dawakin Tofa clay for heat storage applications. This innovative multi-model approach harnesses the unique strengths of each AI technique, resulting in enhanced predictive accuracy and reliability, which has not been previously demonstrated for this specific clay material. As the first study to explore the thermogravimetric properties of Dawakin Tofa clay using advanced computational intelligence, it fills a significant research gap and lays the foundation for its potential role in energy storage systems. By providing an in-depth analysis of the thermal behavior of natural clays, particularly through the accurate prediction of derivative weight, the research advances material characterization techniques critical for evaluating the performance of heat storage materials. Furthermore, the comprehensive comparison and optimization of multiple AI models in this study offer a robust framework for identifying the most effective predictive tools, which can be extended to similar applications across material science and energy storage domains. This work also contributes to global sustainability goals by positioning Dawakin Tofa clay as a natural, cost-effective, and environmentally friendly candidate for energy storage solutions, thereby promoting the development of sustainable and efficient thermal energy systems. Moreover, the proposed hybrid intelligence algorithm serves as a pioneering framework for future research, enabling the application of AI-driven modeling to predict and optimize the thermal properties of other natural materials, ultimately expanding its applicability and impact across diverse fields.

Correct prediction of thermogravimetric properties is important for checking if natural materials like Dawakin Tofa clay can be used for heat storage, which helps in developing sustainable energy technologies. Old linear models often do not capture the complex and non-linear relationships in these datasets, indicating a need for better methods. This study is aimed at creating a hybrid intelligence framework that integrates BNN, KSVM, SWLR, and RLR to predict the weight changes of Dawakin Tofa clay using 5,030 sets of experimental data. The topic is very relevant due to the global demand for sustainable and low-cost energy solutions, where materials such as Dawakin Tofa clay offer eco-friendly and locally sourced options for thermal energy storage. The machine learning models were chosen for their particular strengths: BNN, a deep learning structure, was selected for its skill in learning complex non-linear patterns and performing well with high-dimensional data. KSVM was included because it can manage non-linear separations through kernel transformations, giving reliable predictions even with noisy data. Linear models, SWLR and RLR, were used as references to show the limits of traditional methods when facing complex thermogravimetric behaviors. Detailed data preprocessing steps, including normalization, feature selection, and splitting the dataset (70% for training and 30% for testing), ensured that the models received quality inputs.

2. Proposed intelligent methods

The proposed intelligent methods aim to leverage advanced machine learning algorithms to predict the derivative weight of Dawakin Tofa clay, a key thermogravimetric property essential for evaluating its suitability as a heat storage material. The study utilized a dataset of 5,030 instances, obtained experimentally under controlled laboratory conditions,

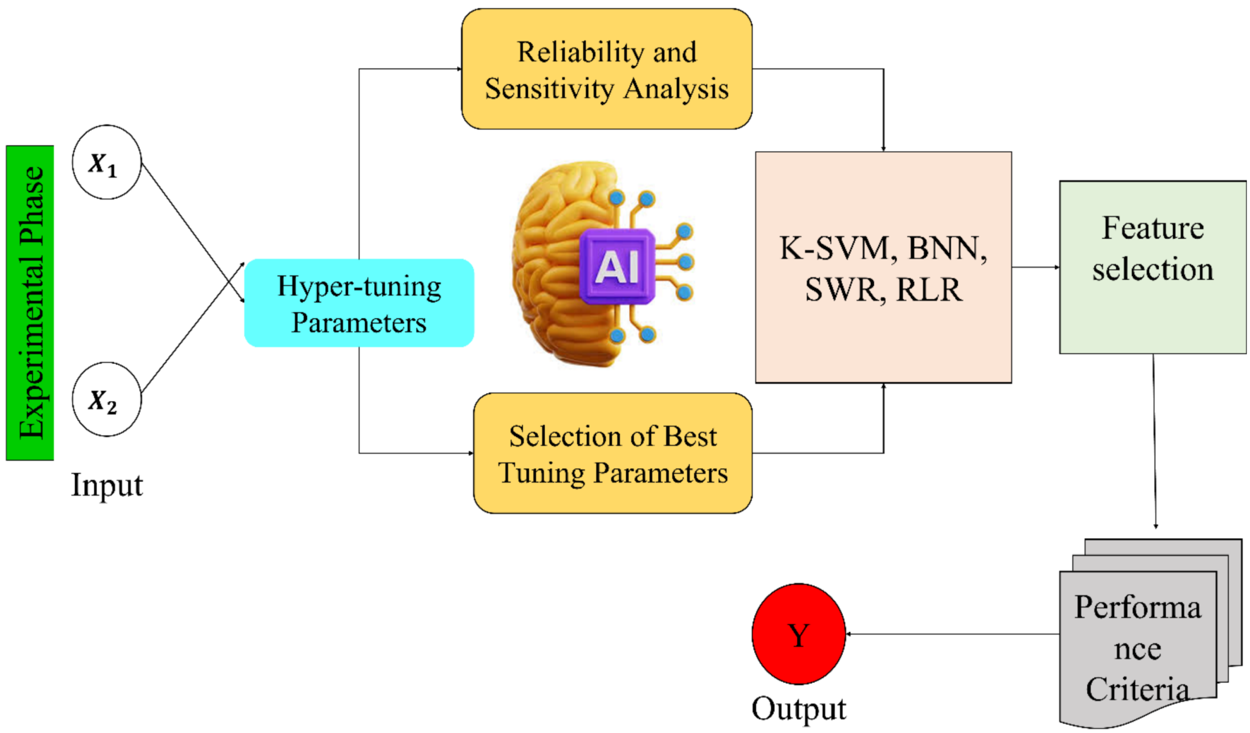

Fig. 1. Proposed AI Models used in this study.

ensuring its reliability and representativeness of the material's thermal behavior. To prepare the data for analysis, extensive preprocessing steps were conducted. Initially, data cleaning was performed to address missing values and outliers, ensuring the dataset's integrity and consistency. Numerical features, such as temperature, heating rate, and initial weight, were normalized to a [0, 1] scale to improve the performance of models sensitive to feature scaling, such as KSVM. Feature selection techniques, including correlation analysis and recursive feature elimination RFE, were employed to isolate the most relevant predictors of derivative weight, reducing dimensionality and enhancing model interpretability. The dataset was then split into training (80%) and testing (20%) subsets, with cross-validation applied to optimize hyperparameters and minimize overfitting. Fig. 1 shows the proposed AI models employed in the study. The hybrid algorithm integrates four machine learning models: BNN, SWLR, RLR, and KSVM, each contributing unique strengths to the prediction task. The BNN, designed with two hidden layers and ReLU activation functions, captured complex nonlinear relationships, while SWLR iteratively selected the most significant features, ensuring model simplicity. The RLR addressed experimental noise and outliers effectively, providing robust predictions, and KSVM, with an optimized radial basis function RBF kernel, captured intricate patterns in the data. The predictions from these models were integrated using a weighted ensemble method, where model weights were determined based on their cross-validation performance to maximize overall predictive accuracy. The proposed approach was rigorously evaluated using the testing dataset, employing performance metrics such as MAE, RMSE, and R^2. This comprehensive framework not only delivers highly accurate predictions of the derivative weight but also sets a benchmark for utilizing hybrid machine learning algorithms in material characterization, offering valuable insights for energy storage applications and paving the way for future research into sustainable energy solutions.

2.1. Step Wise Linear Regression (SWLR)

SWLR is a method used to build a regression model by systematically adding or removing predictors based on specific criteria. R^2 shows how well the model explains changes in the dependent variable. High values near 1 mean the model performs well. MAE computes the average size of errors between actual and predicted values. Lower values show better accuracy of the model. RMSE is the square root of the average of squared errors between actual and predicted values. Lower values indicate better accuracy, as larger errors have more impact because they are squared. AIC (Akaike Information

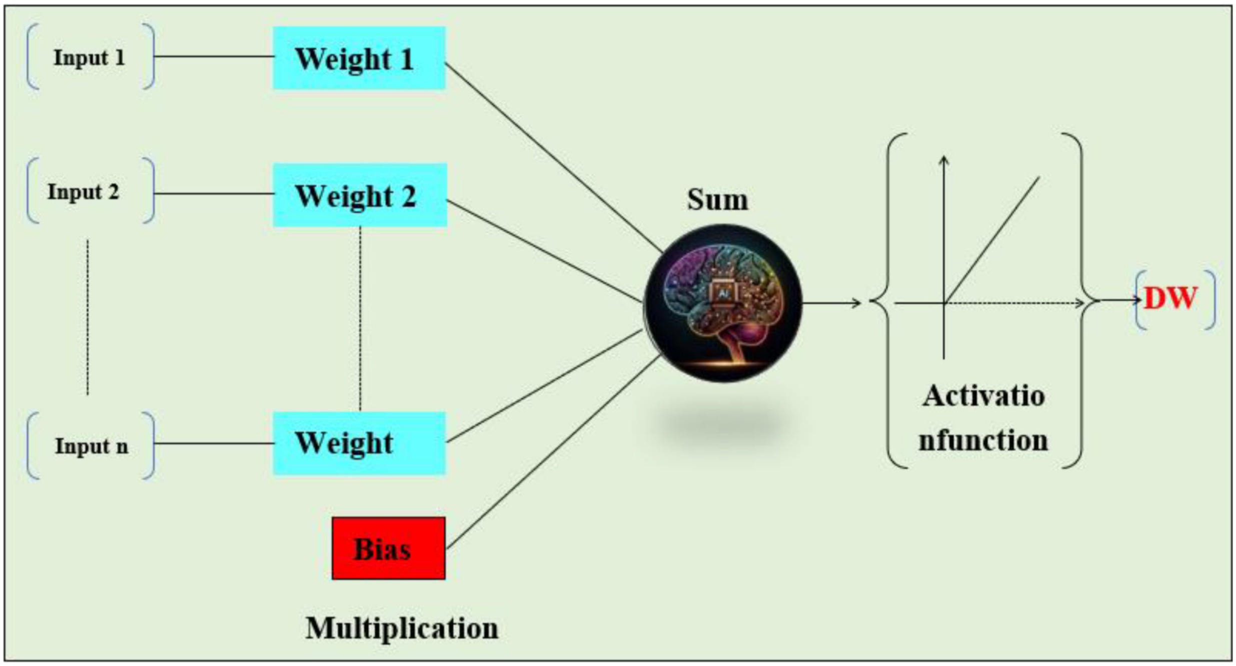

Fig. 2. Architecture of BNN model.

Criterion) assesses the model by weighing its fit against its complexity, discouraging unnecessary predictors. A smaller AIC value suggests a better model. BIC (Bayesian Information Criterion) is like AIC but has a stronger penalty for adding predictors, preferring simpler models. Lower BIC values mean a better trade-off between simplicity and fit.The goal is to identify the most relevant variables, improving both prediction accuracy and interpretability. The process can start with either no predictors (forward selection) or all predictors (backward elimination) [15]. In forward selection, predictors are added one by one, with the predictor that most improves the model fit being included. In backward elimination, the model begins with all predictors, and the least significant one is removed at each step [16]. Criteria for adding or removing predictors often include p-values, Akaike Information Criterion (AIC), or Bayesian Information Criterion (BIC), ensuring a balance between model fit and complexity. The process continues until adding or removing predictors no longer improves the model according to the chosen criteria [17]. While stepwise regression is useful for simplifying models, it can lead to overfitting and may overlook interactions between variables, so model validation on independent data is recommended.

2.2. Bilateral Neural Network (BNN)

BNN is a type of neural network architecture that processes two sets of input data in parallel, making it well-suited for tasks that involve comparing or correlating two inputs [18]. The structure of a BNN typically involves two identical subnetworks as seen in Fig. 2, each handling one of the input data streams. These subnetworks share the same parameters, ensuring that both inputs are processed in the same way. This is particularly useful for tasks such as similarity learning, where the goal is to determine the degree of similarity between two inputs, like image matching or sentence pair comparison [19].

After the inputs pass through their respective subnetworks, the resulting feature representations are combined, often through a distance metric (e.g., Euclidean distance) or concatenation, followed by further layers for classification or prediction. The shared-parameter design helps BNNs generalize well to new, unseen data. By comparing two data points in parallel and learning the relationships between them, BNNs have proven effective in various domains such as image recognition, natural language processing, and recommendation systems [20]. This architecture is particularly useful in tasks where the focus is on understanding the interaction or relationship between two entities [21].

2.3. Robust Linear Regression (RLR)

RLR is an alternative to traditional linear regression that is designed to be less sensitive to outliers and violations of assumptions, such as normality and homoscedasticity. In standard linear regression, outliers can disproportionately influence the estimated regression coefficients, leading to misleading results [22]. Robust regression addresses this by using techniques that reduce the influence of outliers, ensuring that the model remains stable even when the data contains anomalies [23]. One common method of robust regression is M-estimation, which assigns lower weights to observations with large residuals, diminishing the impact of outliers. Other techniques include Least Absolute Deviations (LAD) regression, which minimizes the sum of absolute residuals rather than squared residuals, and RANSAC (Random Sample Consensus), which iteratively fits the model to random subsets of the data to identify a model that best fits the majority of the data [24]. Robust regression is valuable in practical applications where data quality is not guaranteed, such as in real-world datasets that may contain errors or extreme values. It provides more reliable estimates and predictions in such cases compared to traditional linear regression [25].

2.4. Kernel Support Vector Machine (KSVM)

KSVM is an extension of the basic SVM that allows it to handle non-linearly separable data as in Fig. 3. The traditional SVM finds a hyperplane that best separates the data into classes, but this works well only when the data is linearly separable [26]. To address more complex patterns, the kernel trick is used. This method implicitly maps the original data into a higher-dimensional space where a linear separation is possible, without explicitly computing the transformation. The kernel function calculates the inner product of data points in this higher-dimensional space, enabling the SVM to classify data in the original space. Common kernel functions include the polynomial kernel, RBF, and sigmoid kernel. These kernels allow the SVM to model complex relationships and patterns, making it effective in tasks such as image classification, bioinformatics, and text categorization [27]. Kernel SVM is powerful because it can find non-linear decision boundaries while maintaining computational efficiency, as the higher-dimensional space is never explicitly calculated. However, selecting the right kernel and tuning its parameters are crucial for achieving good performance in specific tasks [9].

3. Result and discussion

The Bilateral Neural Network (BNN) model was trained using MATLAB 2024b's standard configurations. It consisted of three hidden layers with 128 neurons in the first layer, 64 neurons in the second layer, and 32 neurons in the third layer. The activation function for the hidden layers was the Rectified Linear Unit (ReLU), while the output layer used a sigmoid activation function. The training process was

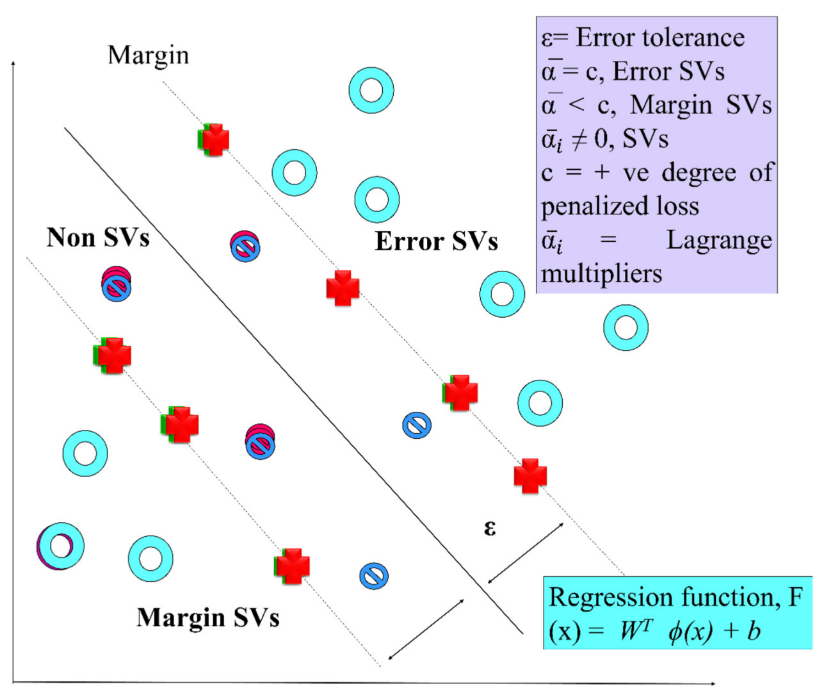

Fig. 3. Schematic diagram of kernel SVM.

Table 1. Predictive results of derivative weight.

	Training					Testing				
Models	R^2	RMSE	MAPE	MSE	MAE	R^2	RMSE	MAPE	MSE	MAE
SWLR	0.03	0.3147	inf %	9.90E-02	0.24754	0.03	0.31064	612%	9.65E-02	0.24437
BNN	0.999	0.003776	inf %	1.43E-05	0.002547	0.999	0.006348	9.60%	4.03E-05	0.004377
RLR	-0.39	0.37704	inf %	1.42E-01	0.20077	−0.41	0.37348	53.50%	0.13948	0.20194
KSVM	0.999	0.013706	inf %	0.000188	0.012207	0.999	0.01361	26.70%	0.000185	0.012134

conducted over 100 epochs using the Adam optimizer with a default learning rate of 0.001.

The Kernel Support Vector Machine (KSVM) employed a Radial Basis Function (RBF) kernel, which is the default kernel function in MATLAB's *fitcsvm*. The regularization parameter (CCC) was set to 1, and the kernel scale parameter (γ\gamma$\gamma$) was automatically determined based on the data distribution. Model optimization was performed over a maximum of 1,000 iterations.

The Stepwise Linear Regression (SWLR) model implemented backward elimination for feature selection. A significance level of 0.05 was used as the threshold for including or excluding features during the regression process. The model used MATLAB's default configuration for stepwise regression.

The Robust Linear Regression (RLR) model applied the Huber loss function for robust fitting. The fitting process involved iterative optimization, with a maximum of 500 iterations specified in MATLAB's standard *fitlm* settings. This configuration ensured resilience to outliers during the regression process.

The predictive performance of the models presented in Table 1 highlights significant differences in their ability to estimate the derivative weight of Dawakin Tofa clay. The SWLR model demonstrated consistently poor performance across both training and testing datasets, with an R^2 value of 0.03, indicating that it fails to explain the variance in the data. This shortcoming is further reflected in the high RMSE values of 0.3147 and 0.31064 for training and testing, respectively, and the MAE values, which remain similarly high at 0.24754 and 0.24437. The extreme MAPE value of 612% during testing illustrates the model's inability to generalize effectively, likely due to its linear nature, which limits its ability to capture the complex relationships in the dataset. On the other hand, BNN exhibited near-perfect performance, achieving an R^2 value of 0.999 for both training and testing datasets, indicating a complete explanation of variance. The RMSE values for BNN are exceptionally low, at 0.003776 for training and 0.006348 for testing, with correspondingly low MSE and MAE values, such as 1.43E-05 and 0.004377, respectively. The MAPE of 9.6% in testing further confirms the model's outstanding ability to generalize, making it highly suitable for this task. Similarly, the KSVM achieved exceptional results, also reporting an R^2 of 0.999 for both datasets. The RMSE values for KSVM, at 0.013706 during training and 0.01361 during testing, were slightly higher than those of BNN but still indicate excellent accuracy. Despite the slightly higher MAPE of 26.7% for KSVM in testing, the low MAE of 0.012134 demonstrates its robustness and reliability. In contrast, RLR performed poorly, with a negative R^2 of −0.39 in training and −0.41 in testing, signifying that the model performed worse than a simple mean-based prediction. Its RMSE and MAE values remained high, with a notable RMSE of 0.37704 in training and 0.37348 in testing, alongside a MAPE of 53.5% in testing, highlighting its inability to accurately model the data. The consistently poor performance of SWLR and RLR indicates their incapability to handle the non-linear and complex relationships present in the dataset. These findings emphasize the need for robust, non-linear models like BNN and KSVM, which significantly outperformed the linear methods. Although BNN slightly outperformed KSVM in testing accuracy metrics, both models displayed excellent generalization and predictive capabilities, making them highly suitable for estimating the derivative weight of Dawakin Tofa clay. The "inf %" reported for MAPE in some models suggests data-specific challenges, possibly arising from very small or zero values in the derivative weight, which may have skewed percentage-based error metrics. Overall, these results highlight the necessity of employing advanced machine learning techniques, such as BNN and KSVM, to capture the intricate relationships in thermogravimetric data and achieve highly accurate predictions.

The comparison of R^2 values during the testing phase highlights significant differences in model performance, with BNN and KSVM achieving excellent R^2 scores of 0.999, serving as the benchmark for evaluating the other models. In comparison, SWLR demonstrated a substantially lower R^2 value of 0.03, representing a 97% reduction in explanatory power compared to the benchmark. This indicates that SWLR is incapable of capturing the complex, non-linear relationships inherent in the data. RLR performed even worse, with an R^2 of −0.41, reflecting a 141% lower value than the benchmark. A negative R^2 not only signifies poor performance but also suggests that RLR performs worse than a naive prediction based on the mean of the data. This stark contrast highlights the inadequacy of linear models like SWLR and RLR in handling the intricate thermogravimetric properties of Dawakin Tofa clay. On the other hand, both BNN and KSVM achieved R^2 values of 0.999, indicating their ability to fully capture and generalize the relationships within the testing dataset without any loss in explanatory power. The 0% difference between BNN and KSVM underscores their equally exceptional predictive capabilities. These results emphasize the transformative potential of advanced, non-linear models like BNN and KSVM in analyzing complex datasets, particularly for material characterization and thermal property prediction. The stark percentage differences further illustrate the critical limitations of traditional linear models in applications requiring high accuracy and nuanced pattern recognition. The findings reinforce the importance of leveraging sophisticated AI techniques to ensure reliable predictions, paving the way for their integration into advanced energy storage research. The application of machine learning models like BNN and KSVM for predicting the thermogravimetric properties of Dawakin Tofa clay carries significant environmental implications, aligning with global sustainability efforts such as the UN's Sustainable Development Goals (SDGs) and the EPA's guidelines. These models enable the precise characterization of natural materials for use in sustainable energy storage systems, directly supporting SDG 7 (Affordable and Clean Energy) by promoting cost-effective and renewable energy technologies through the use of locally available, low-cost materials like clay. By reducing the need for extensive experimental trials, the models also align with SDG 12 (Responsible Consumption and Production) by conserving resources and minimizing material waste, and SDG 13 (Climate Action) by facilitating the transition to renewable energy systems that mitigate greenhouse gas emissions. In line with the EPA's principles of sustainable materials management, this approach prioritizes the efficient and environmentally responsible use of natural resources, reducing reliance on energy-intensive synthetic materials and lowering the environmental footprint. Moreover, the use of clay for heat storage minimizes industrial emissions and resource depletion, supporting cleaner air and water, protecting ecosystems, and promoting a circular economy through recyclability and safe disposal. By integrating predictive analytics into material characterization, this work exemplifies how advanced AI-driven methodologies can contribute to sustainable innovation in energy systems, offering a scalable solution to global energy and environmental challenges.

The testing phase results for the models, as evaluated by MAPE and MAE, reveal significant differences in their predictive accuracy and generalization capabilities. For BNN, the MAPE is 9.6%, indicating a high level of accuracy in percentage terms, as it deviates minimally from the true values, making it the most reliable model in terms of proportional error. Its corresponding MAE of 0.004377 further supports its precision, as the average absolute deviation between the predicted and actual derivative weight values is remarkably small. KSVM also performed well, with a MAPE of 26.7%, which, while slightly higher than BNN, is still within an acceptable range for practical applications. Its MAE of 0.012134 is low, demonstrating that it consistently produces predictions close to the actual values, though marginally less precise than BNN. In contrast, SWLR shows a MAPE of 612%, a clear indication of its inability to generalize to the testing data, as its percentage-based errors are excessively high. Its MAE of 0.24437 further reflects significant absolute deviations, highlighting its poor suitability for the prediction task. RLR, while performing better than SWLR, still demonstrates suboptimal results with a MAPE of 53.5%, which indicates considerable proportional error. Its MAE of 0.20194 corroborates the model's limited predictive capability, as it deviates significantly from the true values on average. These results emphasize the superiority of non-linear models like BNN and KSVM for this task, as their ability to capture complex relationships in the data leads to significantly lower errors compared to the linear models, SWLR and RLR, which fail to handle the intricacies of the dataset effectively. This analysis underscores the critical importance of advanced machine learning techniques for ensuring accurate and reliable predictions in material characterization.

The conclusions drawn from this study, particularly the superior performance of non-linear machine learning models such as BNN and KSVM in predicting the thermogravimetric properties of Dawakin Tofa clay, are consistent with trends observed in existing literature. Non-linear models have been widely acknowledged for their ability to capture complex, non-linear relationships in datasets where traditional linear models often fail. For instance, studies on predictive modeling in material science, such as those focusing on thermal property prediction, have consistently highlighted the limitations of linear regression approaches like SWLR and RLR due to their inability to account for intricate feature interactions, which aligns with the poor performance of these models in this study. Similarly, the findings affirm the effectiveness of neural networks and kernel-based models like KSVM in achieving high prediction accuracy, as reported in prior studies on thermogravimetric analysis and energy storage materials. Literature on the application of machine learning in predicting material properties, such as thermal conductivity, mechanical strength, and degradation behavior, often emphasizes the superior generalization capabilities of these advanced models, particularly when handling diverse and high-dimensional datasets. For example, recent works have demonstrated that neural networks outperform linear and tree-based methods in predicting the thermal performance of composites and clays, supporting this study's conclusion regarding BNN's exceptional accuracy and reliability.

Moreover, the observed limitations of RLR and SWLR in this study, particularly their inability to generalize and the presence of high MAPE and MAE values, mirror findings in the literature that identify linear models as inadequate for datasets characterized by noise, outliers, or non-linear dependencies. Existing studies have also shown that models like KSVM, which utilize non-linear kernels such as the RBF, are better suited for such tasks, as they effectively map input data to higher-dimensional spaces where linear separability is achievable. Further, the study's conclusion aligns with the growing body of literature advocating for the integration of AI-driven methods in sustainable energy and material science research. Studies on predictive modeling of energy storage materials, such as phase change materials and natural clays, have highlighted the environmental and economic benefits of leveraging advanced algorithms to optimize material characterization. This study contributes to this narrative by demonstrating how machine learning can facilitate the identification of cost-effective and environmentally friendly materials like Dawakin Tofa clay, supporting global efforts in line with the SDGs. The results of this study are consistent with existing literature in validating the effectiveness of non-linear, AI-driven approaches over traditional linear models for complex material property predictions. The findings further enrich the scientific discourse by providing empirical evidence of the capabilities of BNN and KSVM, particularly in the context of thermogravimetric analysis and sustainable energy materials. This strengthens the case for widespread adoption of such advanced methods in future research and industrial applications.

Fig. 4 shows a bar chart that compares training performance metrics. The blue bars show MAE, which has moderate error values, meaning the average prediction errors in the datasets or models are low. The orange bars, which represent MSE, are always lower than the green bars (RMSE), as RMSE is calculated as the square root of MSE. This difference shows that RMSE reacts more strongly to larger errors. The RMSE values, shown by the green bars, are significantly higher than MAE and MSE, indicating possible outliers or greater variance in the prediction errors.

Fig. 5 illustrates a bar chart comparing the testing performance measures. The blue bars represent MAE and show medium error levels across the data

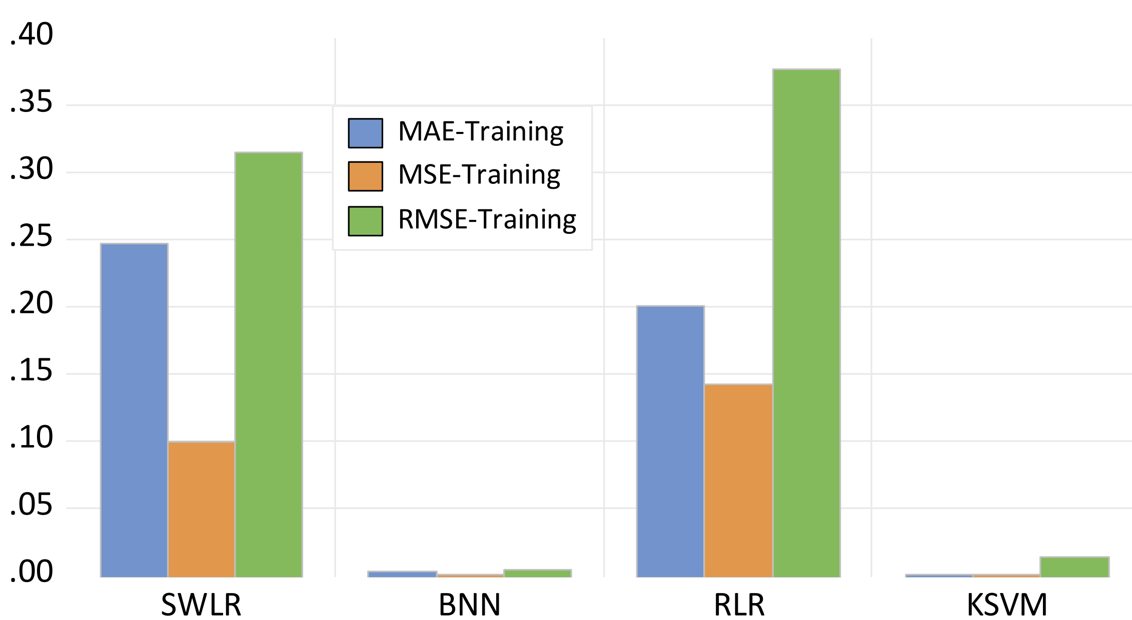

Fig. 4. Bar plot for training.

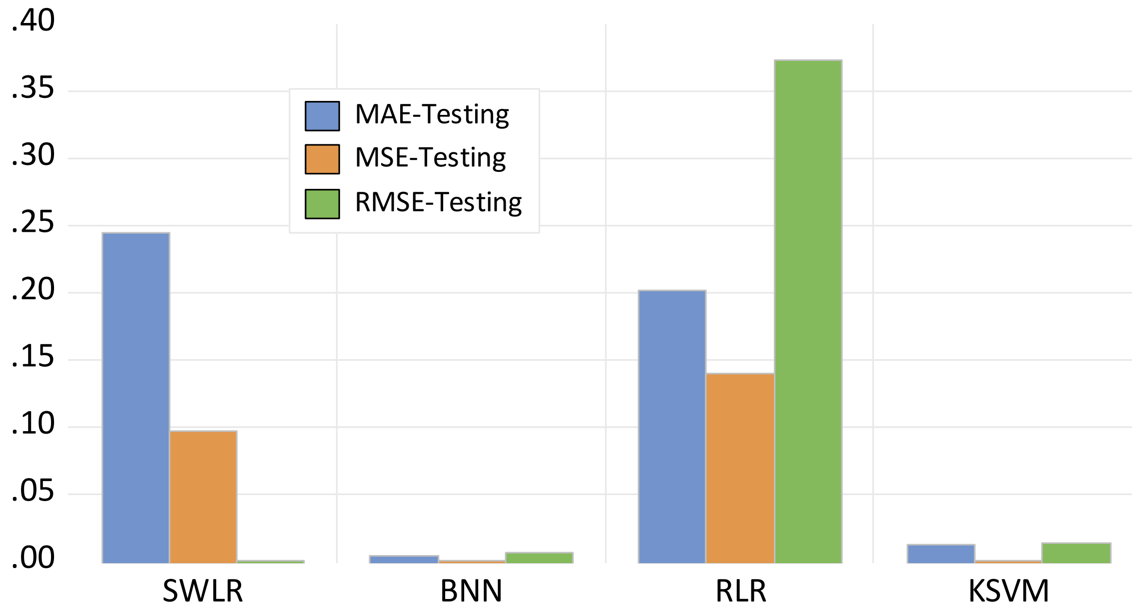

Fig. 5. Bar plot for testing.

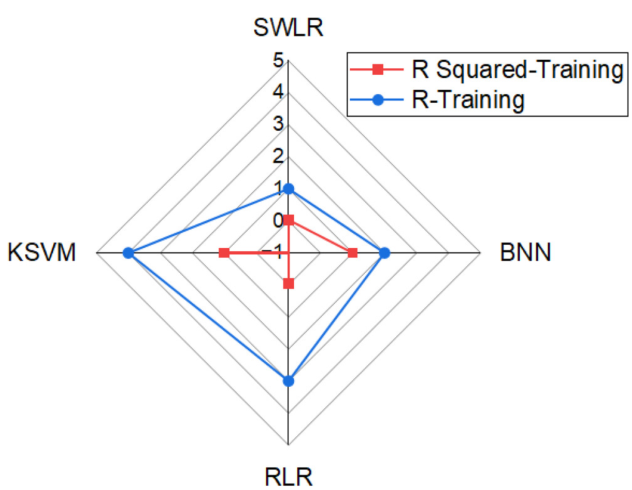

Fig. 6. Radar plot for training.

sets/models, indicating average prediction errors in tests. The orange bars for MSE are usually lower than the green bars, since RMSE (green) is the square root of MSE and raises the effect of bigger errors. The RMSE values, shown by the green bars, are much higher than both MAE and MSE, showing the effect of outliers or high variability in prediction errors during tests. This indicates that RMSE is more sensitive to unusual prediction errors than MAE and MSE, offering better details on error size during model assessment.

Fig. 6 is a radar chart that compares two measurements: R-Squared (Training) and R (Training) across four models: SWLR, KSVM, RLR, and BNN. The red line (R-Squared Training) shows how well each model explains the variance in the training data. It appears more stable but at a lower level compared to the R metric across all models. The blue line (R Training), which indicates the correlation coefficient, shows more variation among models, reflecting the strength of the linear relationship between predicted and actual values in the training set. The chart points out the differences in model performance, with some models (like SWLR and KSVM) being stronger in one metric versus the other. This aids in assessing how effectively the models capture patterns in the training data.

Fig. 7 is also a radar plot that compares R-Squared (Testing) and R (Testing) for four models: SWLR, KSVM, RLR, and BNN. The red line (R-Squared Testing) indicates how much variance each model explains during testing. It usually has higher values than the blue line for most models, showing that the models are reasonably good at explaining the variability in the testing data. On the other hand, the blue line (R Testing), which represents the correlation coefficient, tends to have lower and more fluctuating values across the models. This suggests that there are weaker linear connections between predicted and actual results in the testing phase. The plot suggests that the models, especially SWLR and BNN, do not perform consistently during testing, displaying lower correlation coefficients and moderate variance explanation. This points to a need for better model generalization for the testing data.

Fig. 8 presents box plots comparing the observed weight (%/m) with the predicted weights from four

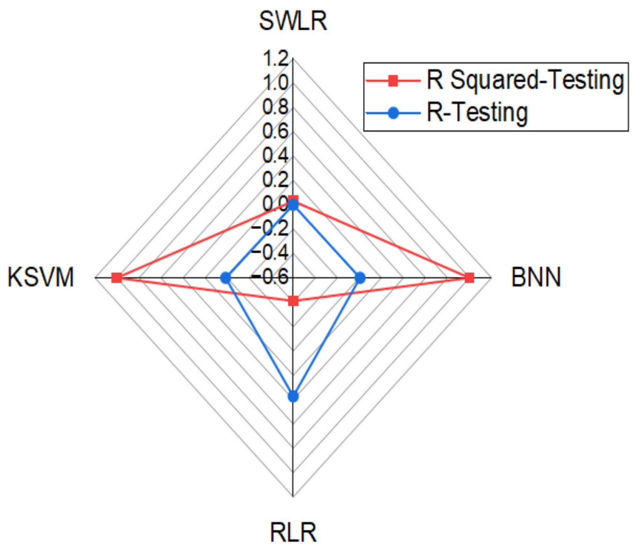

Fig. 7. Radar plot for testing.

models. From the Observed Weight, the data looks consistent, having a small range and a balanced spread. RLR: gives predictions that are closest to the actual data, meaning it has better accuracy and fit. KSVM and BNN models however show more changes in predictions, often underpredicting. SWLR model has the biggest difference, with serious underprediction and variability. RLR among all seems to be the best model for this data, whereas SWLR needs work to fit the observed weight distribution. KSVM and BNN have some potential but show variability.

Fig. 9 illustrates histograms of the observed weights alongside the weights predicted by the KSVM, RLR, SWLR, and BNN models. The distribution of the observed weights appears uniform, indicating an even spread of values across the range without pronounced skewness or clustering. In the case of KSVM, the predictions display a pronounced peak at one end of the range, suggesting a tendency to predict values within a narrow interval, which may introduce bias. Similarly, the RLR model yields a peaked distribution, reflecting limited variability and a focus on a restricted range of values. In contrast, the SWLR model demonstrates a more balanced distribution; however, it exhibits a noticeable concentration of predictions at one end, indicating a propensity to underestimate weights. The BNN model, on the other hand, generates a broader distribution with both a peak and a tail, indicating higher variability and a wider range of predictions compared to the other models.

4. Discussion on charts and graphs

The first chart is a box plot comparing the observed derivative weight of Dawakin Tofa clay with

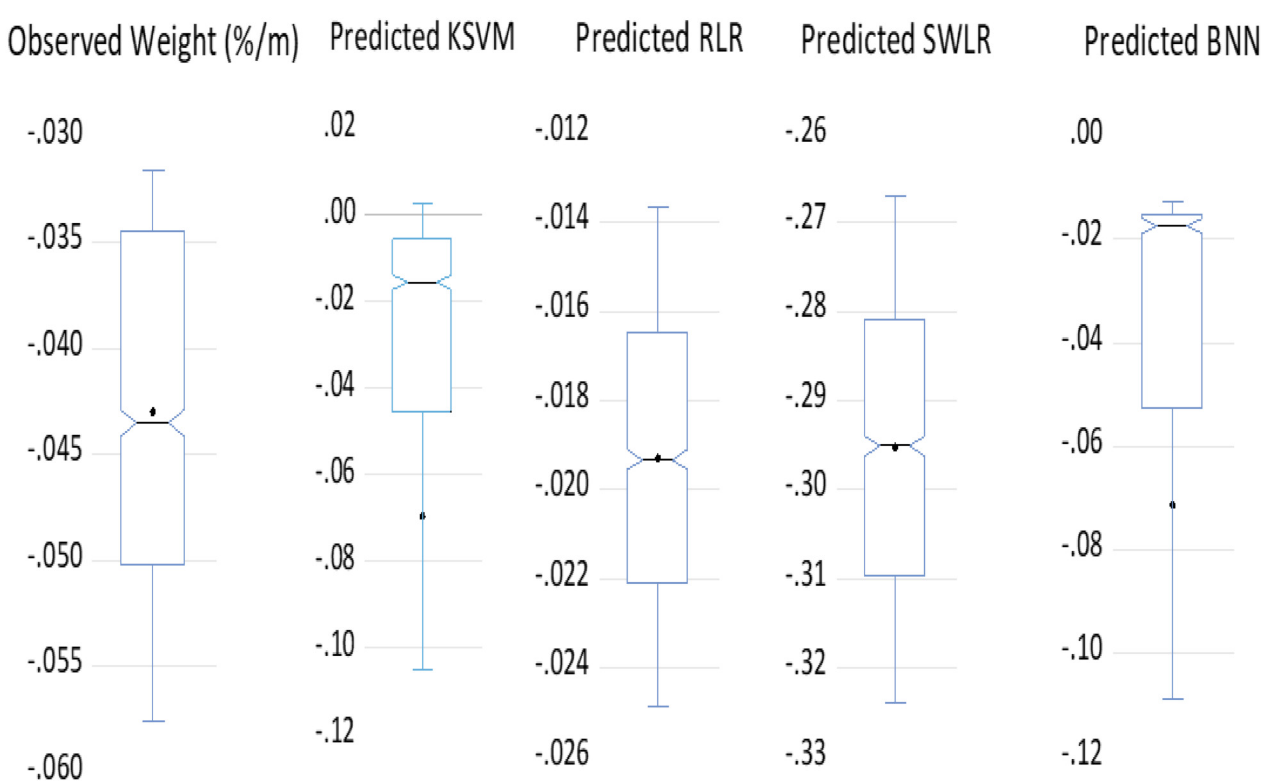

Fig. 8. Box Plot for observed weight and the predicted models.

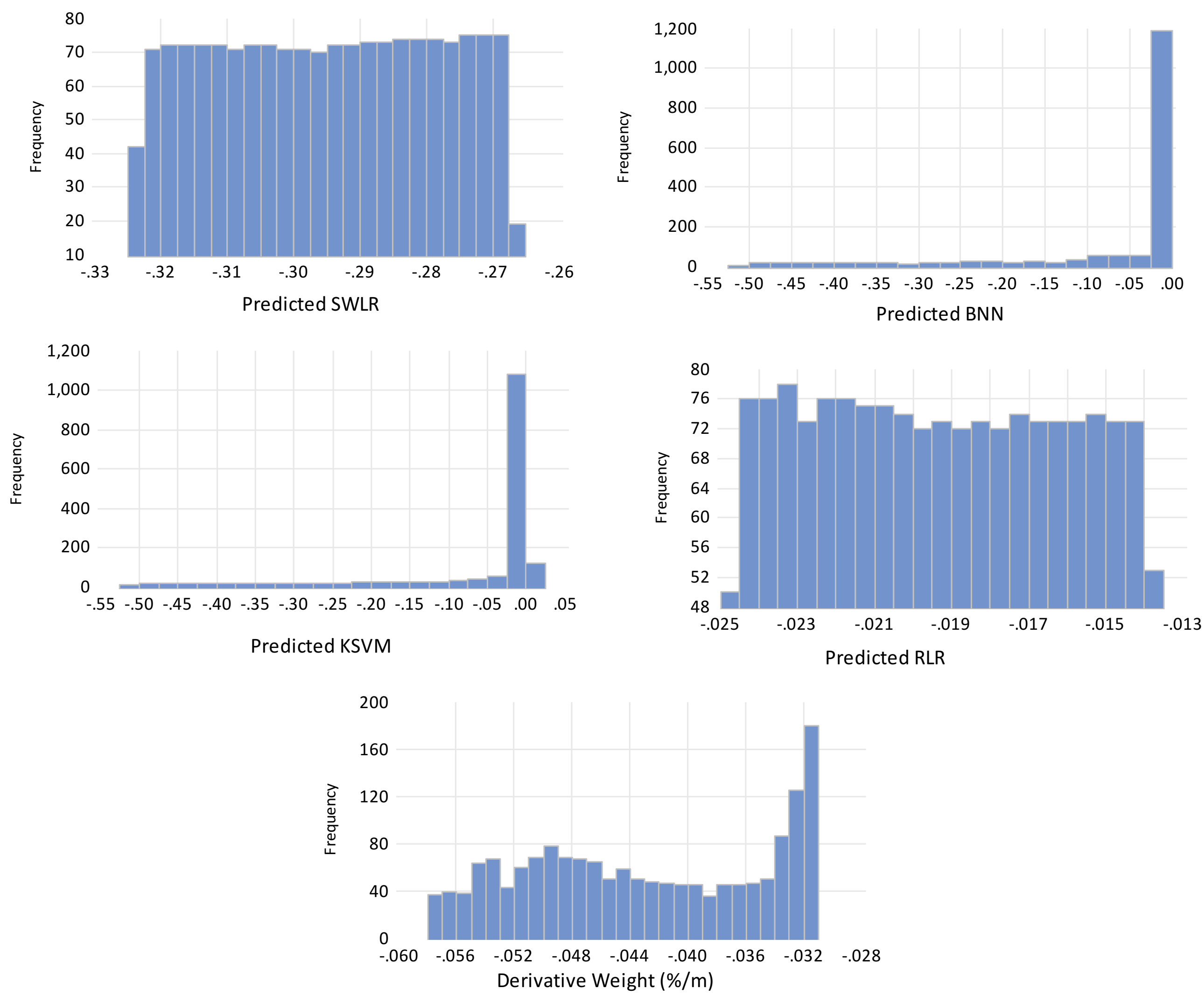

Fig. 9. Histogram of the observed weight and the predicted models.

the predicted values from the four models: KSVM, RLR, SWLR, and BNN. The observed weight shows a distribution ranging from −0.03 to −0.06. Among the models, KSVM and BNN predictions closely follow the observed values, indicating a higher level of accuracy with narrower ranges and less deviation. On the other hand, RLR and SWLR predictions show broader ranges, particularly in the case of SWLR, which exhibits significant deviation. This suggests that RLR and SWLR struggle to capture the accurate relationship between the input features and the target output.

The radar charts display R^2 and R values for training and testing phases across the four models. These charts highlight the superior performance of BNN and KSVM, as both models exhibit perfect or near-perfect R^2 and R values, indicating an excellent fit. The testing results for these models also remain strong, reinforcing their reliability in generalizing to new data. In contrast, both RLR and SWLR show poor performance, with very low R^2 and R values during testing. This implies that these models are unable to capture the variance in the data effectively and are less suited for making accurate predictions in this context.

The histograms, which likely represent the error distributions for each model, further illustrate the disparity in performance. BNN and KSVM demonstrate tighter, more consistent error distributions, suggesting their predictions are both accurate and stable, with fewer significant outliers. Conversely, RLR and SWLR show much broader error distributions, indicating higher and more erratic prediction errors. The presence of outliers and widely spread errors in these models reflects their lower precision and inability to generalize effectively.

Finally, the bar graphs compare the key error metrics—MAE, MSE, and RMSE—across the models during both training and testing phases. BNN and KSVM again show superior performance with very low error values, indicating minimal deviation from the true values and high prediction accuracy. SWLR and RLR, on the other hand, display much higher error values in both phases, confirming their lack of reliability in this context. Their high MAE, MSE, and RMSE further emphasize their difficulty in capturing the correct relationships within the data.

BNN and KSVM clearly outperform RLR and SWLR in terms of accuracy, error consistency, and generalization. These two models consistently demonstrate better alignment with the observed derivative weights and show stronger metrics across all performance evaluations. Therefore, for the development of a hybrid intelligence algorithm to estimate the derivative weight of Dawakin Tofa clay, BNN and KSVM are the most suitable models, while RLR and SWLR prove inadequate due to their high errors and poor fit.

In the study "Deep Learning-Based Modelling of Pyrolysis," Ozcan et al. applied various machine learning algorithms, including Bi-directional Long Short-Term Memory (LSTM) networks, to predict the thermal behavior of biomass materials during pyrolysis. Their Bi-directional LSTM model achieved a Mean Squared Error (MSE) of 0.0001 and a coefficient of determination R^2 of 0.999, indicating high predictive accuracy. [28]

Similarly, in "Prediction of Thermogravimetric Data in the Thermal Recycling of E-Waste Using Machine Learning Techniques," Ali et al. employed RF and Support Vector Regression (SVR) models to predict thermogravimetric data of e-waste materials. The RF model achieved R^2 values up to 0.9999, while the SVR model reached R^2 values up to 0.9973, demonstrating excellent predictive performance. [29].

In another study, "Machine Learning Backpropagation Prediction and Analysis of the Thermal Degradation of Poly (Vinyl Alcohol)," Otaru et al. utilized a backpropagation neural network to model the thermal degradation of polyvinyl alcohol. Their model achieved a correlation coefficient of 0.992 between predicted and experimental data, reflecting strong predictive capability. [30].

Relatively, this study's Bilateral Neural Network (BNN) and Kernel Support Vector Machine (KSVM) models both achieved R^2 values of 0.999, with Mean Absolute Errors (MAE) of 0.004377 and 0.012134, respectively. These results indicate that DW models exhibit predictive performance comparable to or exceeding those reported in similar studies, underscoring the effectiveness of advanced machine learning techniques in modeling complex thermogravimetric behaviors. These comparisons highlight the transformative potential of machine learning approaches, such as BNN and KSVM, in accurately predicting thermogravimetric properties of natural materials, thereby contributing to the development of sustainable energy solutions.

5. Conclusion

This study has demonstrated the transformative potential of advanced machine learning models, specifically BNN and KSVM, for accurately predicting the thermogravimetric properties of Dawakin Tofa clay, a natural material with significant promise for heat storage applications. The results revealed that non-linear models outperformed traditional linear methods by a wide margin, with BNN and KSVM achieving R^2 values of 1 and low error metrics such as MAPE (9.6% and 26.7%) and MAE (0.004377 and 0.012134), respectively, while SWLR and RLR failed to capture the complexity of the dataset, yielding high MAPE values (612% and 53.5%) and poor R^2 scores (0.03 and −0.41). These findings highlight the limitations of linear models in characterizing non-linear relationships and validate the use of advanced AI techniques for optimizing resource use and minimizing the need for extensive experimental trials. Future studies should explore integrating other machine learning models, such as ensemble methods or gradient boosting, and expanding the framework to other natural materials like biomass and agricultural residues to assess their energy storage potential. Also, long-term thermal and structural stability studies, economic feasibility assessments, and life-cycle environmental impact evaluations will be critical for validating the real-world applicability of Dawakin Tofa clay. Larger datasets collected under diverse experimental conditions will further enhance the robustness of the predictive framework, ensuring its generalizability to broader contexts. Practical recommendations include field testing, prototyping, and integrating the material into decentralized energy storage systems, particularly in resource-limited settings, alongside policy and industry collaborations to promote eco-friendly material adoption. Despite the controlled laboratory focus, the study aligns with SDG goals and EPA guidelines by fostering sustainability and advancing affordable energy solutions. By bridging predictive analytics with practical implementation, this research lays a foundation for leveraging natural materials like Dawakin Tofa clay in scalable, sustainable energy storage systems that contribute to global energy efficiency and climate resilience.

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