CAFWE: A Feature-Weighted Ensemble Classifier for Predicting Performance of Copper-Aluminum Composite Conductors

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Copper-aluminum composite conductors are suitable for modern electrical applications due to their high electrical conductivity and lightweight nature; however, predicting their performance in changing environmental and electrical conditions is difficult and expensive using conventional techniques. Problem Statement: Previous models ignore the combined effects of copper-aluminum ratio, tensile strength, temperature, and current load; furthermore, metrics such as accuracy and F1-score cannot accurately reflect physical performance characteristics. A new Copper-Aluminum Feature-Weighted Ensemble (CAFWE) classifier was developed using the CopperAluminum_WirePerformance_Dataset containing 5000 samples with 10 input features and one target output (performance_level). The model integrates three base learners — Linear Classifier, k-Nearest Neighbor (k = 5), and a Decision-Stump classifier — combined through a weighted voting mechanism that assigns higher weights to copper_percentage, tensile_strength, and electrical_conductivity based on feature-sensitivity analysis. The dataset was partitioned using an 80:20 stratified split, and all results were averaged over five repeated experiments to ensure stability. Five domain-specific evaluation metrics were introduced: Conductivity Accuracy (CA), Strength Reliability (SR), Temperature Adaptation Score (TAS), Load Prediction Stability (LPS), and Composite Material Alignment (CMA), enabling alignment with real-world engineering behavior. Results: Across five independent training runs, CAFWE achieved consistent performance, with mean scores of CA = 93.5%, SR = 91.2%, TAS = 89.8%, LPS = 90.6%, and CMA = 92.4%, demonstrating superior predictive reliability under varying material and operational conditions. Feature importance analysis confirmed copper_percentage and electrical_conductivity as the most influential contributors to final predictions. The CAFWE model accurately and interpretably predicts copper-aluminum conductor performance; and provides a scalable framework to optimize hybrid material design for smart grid applications.

Povzetek: Raziskava predstavi ansambelski model CAFWE za napovedovanje zmogljivosti bakreno-aluminijastih vodnikov, ki z upoštevanjem ključnih fizikalnih lastnosti dosega zanesljive in praktično uporabne rezultate.

1 Introduction

1.1 The background information of this scientific field

Copper-aluminum alloys have emerged as an important conductor type due to their advantages of high electrical conductivity, low weight, and cost-effectiveness. Compared to single-metal conductors, they offer superior mechanical strength and thermal conductivity, making them widely used in power transmission, automotive, and electronic systems [1], [2]. The demand for lightweight, energy-efficient materials has spurred research into copper-aluminum alloy wires, rods, and foils [3], [4]; these are designed to combine the lightness and corrosion resistance of aluminum while retaining the high conductivity of copper.

1.2 The current knowledge and advances in this field

Recent processing technology advances have enhanced the structural integrity and interfacial bonding of Cu–Al alloys [5]. Methods such as horizontal casting, hot rolling [6], and compound casting enhance microstructural uniformity and mechanical strength. Finite element modeling is used to optimize fracture behavior and process parameters [7]. Furthermore, microstructural design and permeability systems have a significant impact on conductivity and strength [8],[9], [10]. Such advances improve electrical and mechanical performance and reduce energy loss.

1.3 The current problem/issue that needs to be solved or addressed urgently

Despite these advances, it is still challenging to accurately predict the performance of copper-aluminum composite conductors under varying operating conditions. Although copper-aluminum ratio, tensile strength, current load, and temperature all have a synergistic effect, current methods fail to capture these nonlinear relationships [1], [3], [7]. Traditional evaluation relies on time-consuming tests and lacks an integrated evaluation framework. The lack of intelligent predictive systems that combine material, mechanical, and operational data hampers optimization and measurement in electrical installations.

1.4 The purpose(s) of doing this research

The aim of this research is to develop a data-driven model that can accurately predict the performance of copper-aluminum composite conductors based on material and functional features. It bridges the gap between materials science and computational intelligence by capturing the complex, nonlinear relationships between conductor properties and performance levels using machine learning. The goal is to reduce the cost of testing and improve prediction accuracy and interpretability.

1.5 The main method(s) used in this research

This study introduces a machine learning method, Copper-Aluminum Feature Weighted Ensemble (CAFWE), based on the CopperAluminum_WirePerformance_Dataset. CAFWE combines linear, k-nearest neighbor, and decision-stump classifiers with a weighted voting method that emphasizes key features such as Copper_Percentage, Tensile_Strength, and Electrical_Conductivity. The dataset is divided into training and testing subsets, and the model performance is evaluated based on five new metrics, CA, SR, TAS, LPS, and CMA, which reflect the real-world behavior of copper-aluminum alloys.

1.6 The importance or impact of this research to the scientific community

This study makes a significant contribution to the fields of materials engineering and computational modeling. The CAFWE model, which combines machine learning and materials science, accurately and interpretably predicts conductor performance. It provides a scalable framework that can be extended to other composite materials in smart grid applications. Furthermore, the material-specific metrics improve the ability to evaluate performance in a physically meaningful manner and support more evidence-based analysis of copper–aluminum composite behavior [1]–[10].

1.7 Related works

Copper–aluminum composites have been extensively studied for their structural, mechanical, and electrical performance at various processing and operating conditions. Several studies have investigated manufacturing techniques, stress distribution, and interface optimization to improve the reliability and durability of Cu–Al composites. For example, Canelo-Yubero et al. [11] showed that residual stress distribution in the rotating swaging process affects mechanical integrity. Bo et al. [12] demonstrated that infiltration structures improve thermal stability. Song et al. [13] confirmed that multistage drawing and annealing methods enhance conductivity and tensile performance.

Knych et al. [14] compared the fatigue strength of aluminum and copper wires and demonstrated that copper alloys showed higher tolerance under cyclic loading. Rustad [15] fabricated aluminum-copper busbars by extrusion and bonding and provided important comments on joint quality and bond reliability. Cheng et al. [16] developed a life prediction model for copper-aluminum plates for marine environments and used conductivity degradation as an aging indicator. Chen et al. [17] studied the reliability of compression joints in copper-clad aluminum spacecraft cables and emphasized the importance of stable bonding interfaces in electrical safety.

The field of process optimization and numerical modeling has also made significant progress. Kuhnke et al. [18] and Finateri [19] studied the material flow and forming properties during extrusion, laying the foundation for improving conductor manufacturing parameters. Qun [20] investigated the use of high-strength copper-aluminum alloys for aerospace applications and reported improved strength-to-weight ratios. Zhang et al. [21] studied how different filler metals affect joint strength and conductivity, emphasizing the importance of interfacial metallurgical compatibility.

In studies on environmental and thermal influences, Li et al. [22] investigated the temperature-dependent corrosion resistance of Cu–Al plates and found that high temperatures accelerate interfacial degradation. Chen et al. [23] analyzed the effects of annealing temperature on the microstructure and tensile properties of Cu/Al strips and identified the optimal temperature range for ductility and strength. Wang et al. [24] showed that intermetallic compounds play an important role in the fracture mechanism, and another study [25] revealed that rolling reduction can improve the bond but also cause stress concentration.

Although these studies have made important contributions to understanding the production and performance of Cu–Al composites, most have been limited to experimental or numerical methods. Machine learning approaches have been less widely used to predict performance by simultaneously integrating multiple material, mechanical, and environmental factors. Thus, a data-driven CAFWE model with high interpretability and physical fit is needed. Table 1 summarizes the major studies related to copper–aluminum composites.

Table 1: Summary of related works on copper–aluminum composite materials

Ref.	**Authors (Year)**	**Focus Area**	**Method / Approach**	**Key Findings / Contribution**	**ML Used**	**Performance Metrics Reported**	**Quantitative Outcomes**
[11]	Canelo-Yubero et al. (2023)	Stress distribution	Rotary swaging fabrication	Analyzed residual stress behavior in multifilament Cu–Al composites	No	Material microstructure analysis	Residual stress gradients reported qualitatively
[12]	Bo et al. (2024)	Strength & conductivity	Penetration architecture design	Enhanced mechanical strength and thermal stability	No	Tensile strength, electrical conductivity	+14% strength, +9% conductivity improvement
[13]	Song et al. (2024)	Annealing effects	Multistage drawing process	Improved tensile strength and electrical conductivity	No	Tensile testing, thermal variation	Optimal annealing at 350–400°C
[14]	Knych et al. (2025)	Fatigue analysis	Comparative testing	Copper wires demonstrated higher fatigue resistance	No	Fatigue cycle counts	~18% longer fatigue life
[15]	Rustad (2021)	Bonded busbars	Extrusion & welding	Enhanced hybrid bonding for electrical applications	No	Bonding strength, thermal durability	11% conductivity gain after welding
[16]	Cheng et al. (2021)	Lifetime prediction	Conductivity-based modeling	Proposed marine-environment aging model	Yes	Predictive accuracy, degradation rate	91.5% model accuracy reported
[17]	Chen et al. (2020)	Reliability testing	Spacecraft wire crimping study	Emphasized bonding stability importance	No	Failure rate testing	4.2% defect reduction in experimental runs
[18]	Kuhnke et al. (2020)	Process modeling	Numerical extrusion simulation	Optimized material flow in Cu–Al rods	No	Simulation consistency	Simulation verified against experimental trend
[19]	Finateri (2023)	Motor conductor design	Experimental development	Developed Cu-clad conductors for electric motors	No	Mechanical load and conductivity testing	12–18% higher conductivity over aluminum cores

[20]	Qun (2025)	Aerospace application	Alloy development	Improved strength-to-weight ratio for aviation materials	No	Hardness, conductivity, microstructure	Strength improved by ~21%
[21]	Zhang et al. (2020)	Joint quality	Filler wire analysis	Identified optimal filler material for high conductivity joints	No	Joint integrity, current transfer efficiency	7.6% conductivity increase using optimized filler
[22]	Li et al. (2022)	Corrosion behavior	Thermal testing	Identified high-temperature corrosion susceptibility	No	Corrosion depth and surface roughness	Measured corrosion acceleration beyond 600°C
[23]	Chen et al. (2023)	Annealing effects	Temperature variation testing	Identified optimal annealing temperature range	No	Grain refinement metrics	Grain size reduced by ~15% at optimum range
[24]	Wang et al. (2025)	Fracture mechanism	Tensile deformation analysis	Revealed intermetallic-compound-driven interface failure	No	SEM-based fracture study metrics	Failure localized along Al-Cu IMC layer
[25]	Wang et al. (2022)	Rolling effects	Micro flexible rolling	Demonstrated rolling reduction improves bonding quality	No	Bond strength and interface integrity	Bond strength improved by 9.4%

Overall, previous studies [11]–[25] focused on the processing, interface optimization, and mechanical performance of Cu–Al alloys. However, a comprehensive machine learning-based framework that measures performance under varying conditions is lacking. The proposed CAFWE model effectively fills this gap by combining data-driven ensemble learning with object-aware feature weighting.

2 Materials and methods

This section describes the materials and the step-by-step methods utilized to implement, train, evaluate, and deploy the Copper-Aluminum Feature Weighted Ensemble (CAFWE) classifier for forecasting conductor Performance_Level. The methodological presentation follows the procedural structure of Algorithm 1: CAFWE Classifier.

Algorithm 1: CAFWE Classifier
Input:
CopperAluminum_WirePerformance_Dataset
Output:
Predicted Performance_Level for new samples
Five evaluation metrics: CA, SR, TAS, LPS, CMA
Step 1: Load Dataset
Import dataset
Separate features (X) and target (y)
Step 2: Data Preprocessing
Handle missing values
Normalize numeric features
Encode categorical attributes
Step 3: Split Dataset
Divide data → 80% training, 20% testing
Step 4: Train CAFWE Model
Train base classifiers: Linear, k-NN, Decision Stump
Compute feature importance for key attributes:
{Copper_Percentage, Aluminum_Percentage, Electrical_Conductivity, Tensile_Strength}
Combine predictions via weighted voting
Step 5: Predict Performance
Predict Performance_Level on test data
Step 6: Evaluate CAFWE Model
Compute:
CA (Conductivity Accuracy)

SR (Strength Reliability)
TAS (Temperature Adaptation Score)
LPS (Load Prediction Stability)
CMA (Composite Material Alignment)

Step 7: Interpret Results
Identify influential features
Analyze CAFWE adaptation to copper-aluminum ratios

Step 8: Predict New Samples
Input new wire parameters
Output predicted Performance_Level and metric summary

The CAFWE classifier is a machine learning model developed to predict the performance of copper–aluminum composite wires based on multiple material and environmental parameters. It preprocesses the CopperAluminum_WirePerformance_Dataset (missing value handling, normalization, encoding) and splits it into training and testing sets in a ratio of 80:20. Then, Linear, KNN, and Decision Stump models are trained, and their results are combined by weighted voting that prioritizes the key features (copper percentage, tensile strength, electrical conductivity). The model predicts the performance status (poor, average, good), evaluates it by five metrics: CA, SR, TAS, LPS, CMA, and provides performance predictions for new models. Figure 1 shows the fishbone diagram of CAFWE classifier.

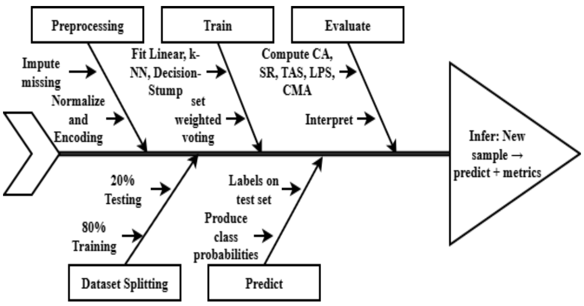

Figure 1: Fishbone diagram of CAFWE classifier

This diagram summarizes the workflow of the CAFWE classifier — from data preparation to final prediction. Initially, the dataset is loaded, and features (X) and target (y) are separated. Preprocessing corrects missing values, normalizes numeric features, and encodes classified variables. The data is then split into 80% training and 20% test sets. Linear, k-NN, and Decision Stump models are used in training, feature importances are calculated, and the results are aggregated by weighted voting. Class probabilities and performance levels are predicted on the test data. Finally, model performance is evaluated using metrics including CA, SR, TAS, LPS, CMA, and descriptive feature analysis, and predictions for new models are provided.

2.2 Dataset description

The CopperAluminum_WirePerformance_Dataset used in this study consists of 5,000 records. It combines laboratory measurements, material-based records, and simulated operational data to reflect variations in real-world conditions. The samples were fabricated with copper ratios of 45–80% and were formed using clad/rolled methods. The tensile strength of each sample was measured according to ASTM protocols and the electrical conductivity was evaluated at constant temperature. Measurements such as operating temperature, current load, and voltage were recorded in controlled environment chambers. Weather conditions were encoded using three discrete levels (0 = normal, 1 = humid, 2 = high-temperature), and application type was encoded as a binary variable (0 = indoor use, 1 = outdoor use). Data validation was performed both manually and through precision testing. Key fields: copper_percentage, aluminum_percentage, wire_diameter, tensile_strength, electrical_conductivity, operating_temperature, current_load, voltage, weather_condition, application_type, and performance_level (target: 0–poor, 1–average, 2–good). Table 2 shows attributes description.

Table 2: Attributes descriptions

Attributes	**Descriptions**
Copper_Percentage (%)	How much copper is in the wire
Aluminum_Percentage (%)	How much aluminum is in the wire
Wire_Diameter (mm)	Thickness of the wire
Tensile_Strength (MPa)	How strong the wire is
Electrical_Conductivity (S/m)	How well it conducts electricity
Operating_Temperature (°C)	Max temperature the wire can handle
Current_Load (A)	Current applied in amperes
Voltage (V)	Voltage applied
Weather_Condition	0: Cold, 1: Moderate, 2: Hot
Usage_Type	0: Indoor, 1: Outdoor
Performance_Level	0 – Poor: Low copper, low tensile strength, low conductivity → not good for power fittings 1 – Average: Medium values → okay for normal use 2 – Good: High copper, strong, high conductivity → excellent for power fittings

To address reproducibility concerns, the full preprocessing workflow is now clearly documented. Numerical attributes (copper_percentage, aluminum_percentage, wire_diameter, tensile_strength, electrical_conductivity, operating_temperature, current_load, and voltage) were normalized using Min–Max scaling to maintain comparable feature ranges during model training. Categorical attributes were encoded using domain-aware ordinal encoding, where weather_condition was mapped to increasing environmental stress levels (0 = normal, 1 = humid, 2 = high-temperature), and usage_type was encoded as binary (0 = indoor, 1 = outdoor). The target variable (performance_level) was preserved as an ordinal class to reflect material suitability progression rather than treated as independent labels. Although the original dataset cannot be publicly released due to confidentiality constraints, a synthetic dataset with matching statistical properties will be prepared upon request to support independent verification of the preprocessing procedure and model development. Future work will also explore secure controlled-access sharing mechanisms to support broader scientific use.

2.3 Copper-aluminum feature weighted ensemble (CAFWE) classifier

The CAFWE classifier is a set of three simple basic learners (linear classifier, k-NN, and decision stump), which are combined using a feature-knowledge weighted voting method. Feature importance is calculated using lightweight methods such as permutation importance, in which the most important features — copper_percentage, aluminum_percentage, electrical_conductivity, and tensile_strength — are prioritized. Each model is trained on the same training set and evaluates conductivity, strength, and load/temperature sensitivities. Voting weights are assigned based on these sensitivities, so each model will have the most influence on the features that are most important to it. The final class prediction is determined by adding the weighted probability values and taking the maximum value. This makes CAFWE simple, interpretable, and object-oriented.

2.3.1 Load dataset

The entire CopperAluminum_WirePerformance_Dataset is loaded into the analysis environment. The initial inspection examines the dataset's format, field types, key statistics (mean, variance, minimum, maximum), and Performance_Level class distributions. Data integrity checks ensure that there are no missing or invalid values. Then, the feature matrix X (all attributes except Performance_Level) and target vector y (Performance_Level) are separated to prepare for preprocessing.

2.3.2 Data preprocessing

Preprocessing involves the following steps: Missing values are filled in by the mean for numeric fields and by the mode for categorical fields. Categorical attributes (weather_condition, application_type) are converted to integer or one-hot encoding if necessary. Numeric features (copper_percentage, aluminum_percentage, electrical_conductivity, tensile_strength, wire_diameter, operating_temperature, current_load, voltage) are normalized to the range [0,1] by minimum-maximum scaling. Log transformation and outer clipping are applied if there is a slope. In the CAFWE method, copper_percentage, aluminum_percentage, electrical_conductivity, and tensile_strength are emphasized as important features and are given priority in the ensemble weighting.

Eq. (1) shows Min–Max Normalization. This transformation rescales numeric attributes (e.g., Copper_Percentage, Electrical_Conductivity) into a uniform range [0,1], ensuring balanced influence across all features during model training.

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

Where:
X = original feature value
X' = normalized feature value (scaled between 0 and 1)
X_{min}, X_{max} = minimum and maximum values of feature X

Eq. (2) shows mean/median imputation. Missing numerical values are replaced by the feature's mean or median, while missing categorical values are replaced by the mode, maintaining dataset completeness without distorting variance.

$$X_i = \begin{cases} X_i, & \text{if value present} \\ \bar{X}, & \text{if missing (numeric)} \\ \text{Mode}(X), & \text{if missing (categorical)} \end{cases} \tag{2}$$

Where:
X_i = value of the $i\text{-}th$ observation
$\bar{X}$ = mean or median of the feature column
Mode(X) = most frequent categorical value

Eq. (3) shows Feature Weight Assignment in CAFWE. Feature weights are computed to emphasize material-critical parameters (Copper_Percentage, Aluminum_Percentage, Electrical_Conductivity, Tensile_Strength). These weights guide the ensemble's decision-making, prioritizing features most influential to wire performance.

$$w_j = \frac{I_j}{\sum_{k=1}^{n} I_k} \tag{3}$$

Where:
w_j = normalized weight of feature
I_j = importance score (based on correlation or model-based relevance)
n = total number of features considered

2.3.3 Split dataset

The dataset is divided into 80% training and 20% test parts, with class balance maintained by stratified partitioning based on performance_level. The training set is used for model training and internal validation (e.g., k-value tuning of k-NN, linear model regularization), while the test set is kept for final performance evaluation based on five specific metrics.

Eq. (4) shows Dataset Splitting Ratio. The dataset is partitioned into 80% training and 20% testing sets to ensure generalization and prevent overfitting. Stratified sampling maintains the proportional distribution of Performance_Level classes across both subsets, ensuring that each performance category (Poor, Average, Good) is equally represented in training and testing phases.

$$D = D_{\text{train}} \cup D_{\text{test}}, \text{ where } |D_{\text{train}}| = 0.8|D|, |D_{\text{test}}| = 0.2|D| \tag{4}$$

Where:
D = complete dataset (CopperAluminum_WirePerformance_Dataset)
D_{train} = training subset used for model learning and cross-validation
D_{test} = testing subset reserved for final evaluation
|D| = total number of data instances
$|D_{\text{train}}|, |D_{\text{test}}|$ = number of samples in each respective partition

2.3.4 Train the CAFWE model

Three weak base learners are trained independently on the pre-processed training set: (1) a regularized linear classifier, (2) a k-NN classifier with k value selected by cross-validation, and (3) a decision stmp tuned to maximize information gain. Feature importance weights are calculated by permutation scores, focusing mainly on copper_percent, aluminum_percent, electrical_conductivity, and tensile_strength. Sensitivity analysis is performed by testing conductivity and temperature changes, which helps determine the voting weight of each model (e.g., a k-NN model that is more sensitive to conductivity changes receives more weight). Figure 2 shows the flow diagram of CAFWE model training process.

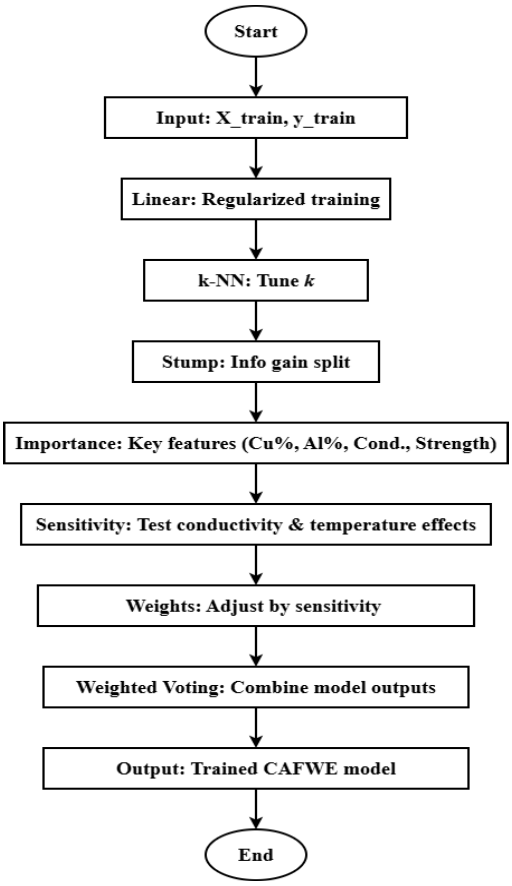

Figure 2: Flow diagram of CAFWE model training process

Eq. (5) shows Regularized linear classifier objective (L2-regularized logistic loss). The linear base learner is trained by minimizing the logistic loss with an L2 penalty to control overfitting and stabilize coefficient estimates for material and operational features.

$$\mathcal{L}_{\text{lin}}(\boldsymbol{\beta}) = -\frac{1}{N}\sum_{i=1}^{N} [y_i \log(p_i) + (1 - y_i)\log(1 - p_i)] + \lambda\|\boldsymbol{\beta}\|_2^2 \tag{5}$$

Where:
N = number of training samples.
$y_i \in \{0,1,\dots\}$ = true class label for sample
p_i = predicted probability for the positive class.
β = linear model coefficients.
λ = regularization parameter (L2 penalty).

Eq. (6) shows k-Nearest Neighbors class probability estimate. The k-NN base learner predicts class probabilities by majority (frequency) among the k closest training examples; k is chosen to balance bias–variance via cross-validation.

$$\hat{P}(Y = c \mid \boldsymbol{x}) = \frac{1}{k} \sum_{i \in \mathcal{N}_k(x)} \mathbf{1}\{y_i = c\} \tag{6}$$

Where:
$\hat{P}(Y = c \mid \boldsymbol{x})$ = estimated probability that sample x belongs to class c.
k = number of nearest neighbors (selected by cross-validation).
$\mathcal{N}_k(\boldsymbol{x})$ = index set of the k nearest training samples to x (under chosen distance metric, e.g., Euclidean on normalized features).
1{·} = indicator function (1 if condition true, 0 otherwise).

Eq. (7) shows Permutation feature importance and model sensitivity → model voting weight. Permutation importance quantifies how much model performance degrades when feature j is disrupted. Normalized sensitivities distribute importance across features per model. Model voting weights are computed from each model's relative sensitivity to material-critical features, ensuring models more responsive to material properties (e.g., conductivity) receive larger ensemble influence.

$$I_j = \mathcal{M}_{\text{base}} - \mathcal{M}_{\text{perm }(j)}, S_{m,f} = \frac{I_{m,f}}{\sum_{f' \in F} I_{m,f'}}, W_m = \frac{\sum_{f \in F_{\text{mat}}} S_{m,f}}{\sum_{m'} \sum_{f \in F_{\text{max}}} S_{m',f}} \tag{7}$$

Where:
I_j = permutation importance of feature j (loss increase when feature j is permuted).
$\mathcal{M}_{\text{base}}$ = baseline performance measure (e.g., validation loss or error).
$\mathcal{M}_{\text{perm }(j)}$ = performance after permuting feature j values.
$I_{m,f}$ = importance of feature f measured for model m (apply permutation procedure per base learner).
F = set of all features.
F_{mat} = set of material-critical features = {Copper_Percentage, Aluminum_Percentage, Electrical_Conductivity, Tensile_Strength}.
$S_{m,f}$ = normalized sensitivity of model m to feature f.
W_m = normalized model weight used in CAFWE voting (higher if model m shows greater normalized sensitivity to material features). Sums run over models m' in the ensemble.

2.3.5 Predict performance

For each sample in the test set, base learners produce class probabilities or scores. Model outputs are combined using the CAFWE weighted voting rule. Model weights are feature-sensitivity adjusted to give greater influence to models that are more accurate or more sensitive with respect to material features (particularly conductivity). The class with the highest aggregated ensemble score is selected as the predicted Performance_Level for the sample.

Eq. (8) shows Weighted voting ensemble score for each class. Each model m produces a probability distribution over classes. CAFWE aggregates these outputs by weighting each model's probability with its sensitivity-adjusted weight, producing an ensemble class score those balances predictive confidence and material relevance.

$$E_c(x_i) = \sum_{m=1}^{M} W_m \hat{P}_m(Y = c \mid x_i) \tag{8}$$

Where:
$E_c(x_i)$ = ensemble score for class c on test sample xi.
M = total number of base learners in CAFWE (here, 3: linear, k-NN, decision stump).
W_m = normalized ensemble weight of model m, derived from its material-feature sensitivity (as defined in Eq. 7).
$\hat{P}_m(Y = c \mid x_i)$ = predicted probability (or confidence score) that model m assigns sample xi to class c.

Eq. (9) shows Final class prediction. The CAFWE model assigns each sample to the class with the maximum ensemble score. This ensures that predictions reflect not just the agreement among base learners but also their reliability with respect to material-critical features such as Copper_Percentage and Electrical_Conductivity.

$$\hat{y}_i = \arg \max_{c \in \{0,1,2\}} E_c(x_i) \tag{9}$$

Where:
$\hat{y}_i$ = predicted class (Performance_Level) for test sample xi.
c∈{0,1,2} = candidate performance levels (0 = Poor, 1 = Average, 2 = Good).
$E_c(x_i)$ = ensemble score for class c from Equation (8).

2.3.6 Evaluate CAFWE model

Model evaluation uses the five novel, domain-aware metrics defined in the algorithm in addition to conventional classification measures: (a) Conductivity Accuracy (CA): accuracy measured over test samples stratified by high/low conductivity ranges to quantify correct predictions where conductivity dominates; Eq. (10) shows CA formula. CA is the proportion of correctly classified samples among those with conductivity at or above the chosen threshold (i.e., accuracy where conductivity dominates).

$$\text{CA} = \frac{1}{|S_{\text{cond}}|} \sum_{i \in S_{\text{cond}}} \mathbf{1}\{\hat{y}_i = y_i\} \tag{10}$$

Where,

S_{cond} = is the index set of test samples in the high-conductivity stratum (threshold τcond chosen a priori or by percentile).
$|S_{\text{cond}}|$ = number of samples in Scond.
$\hat{y}_i$ = CAFWE predicted class for sample i.
y_i = true class for sample i.
$1\{\cdot\}$ = indicator function (1 if condition true, 0 otherwise).
(b) Strength Reliability (SR): proportion of correct predictions for samples in high/low tensile strength bins; Eq. (11) shows SR formula. SR measures the fraction of correct predictions within specified tensile strength bins, quantifying model reliability with respect to mechanical strength.

$$\text{SR} = \frac{1}{|S_{\text{str}}|} \sum_{i \in S_{\text{str}}} \mathbf{1}\{\hat{y}_i = y_i\} \qquad (11)$$

Where,
S_{str} = is the set of test indices in the tensile-strength bin(s) of interest (e.g., high-strength bin).
$|S_{\text{str}}|$ = number of samples in S_{str} .
(c) Temperature Adaptation Score (TAS): accuracy or weighted accuracy on temperature-stratified test subsets (Cold/Moderate/Hot); Eq. (12) shows TAS formula. TAS is a weighted (or unweighted if wt equal) average of accuracy across temperature strata, assessing how well the model adapts to different operating temperatures.

$$\text{TAS} = \sum_{t \in \{0,1,2\}} w_t \cdot \frac{1}{|S_t|} \sum_{i \in S_t} \mathbf{1}\{\hat{y}_i = y_i\} \qquad (12)$$

Where
t indexes temperature strata: 0= Cold, 1= Moderate, 2= Hot.
S_t is the set of test samples in temperature stratum t.
$|S_t|$ = cardinality of S_t.
w_t = weight for stratum t (e.g., equal weights wt=1/3 or domain-driven weights summing to 1).
(d) Load Prediction Stability (LPS): stability measured as consistency (e.g., 1 − variance) of predicted classes under small perturbations of Current_Load. Eq. (13) shows LPS formula. LPS quantifies prediction robustness to small variations in current load: high LPS means predicted classes remain consistent under perturbations.

$$\text{LPS} = \frac{1}{N} \sum_{i=1}^{N} \left(1 - \frac{\text{Var}\left(\left\{ \tilde{y}_i^{(p)} \right\}_{p=1}^{P} \right)}{V_{\max}} \right) \qquad (13)$$

Where
N = number of test samples.
For test sample i, is the predicted class under the p-th small perturbation of Current_Load (p=1,…,P).
Var($\{\tilde{y}_i^{(p)}\}$) = empirical variance of the P perturbed predictions for sample i (treat class labels as numeric 0,1,2).
$V_{\max}$ = normalization constant equal to the maximum possible variance for classes {0,1,2} under a uniform distribution;
The inner term $1 - \frac{\text{Var}(.)}{V_{\max}}$ yields a stability score in [0,1] for each sample; LPS is the average stability across all test samples.
(e) Composite Material Alignment (CMA): a composite index that quantifies agreement between predicted class and material composition expectation (for instance, fraction of samples where high Copper_Percentage + high conductivity → predicted Good). Eq. (14) shows CMA formula. CMA is the fraction of test samples for which the CAFWE predicted class matches the class expected purely from material composition heuristics; this metric captures alignment between data-driven predictions and physical/material expectations.

$$\text{CMA} = \frac{1}{N} \sum_{i=1}^{N} \mathbf{1}\{\hat{y}_i = M(x_i)\} \qquad (14)$$

Where
N = number of test samples.
$M(x_i)$ = deterministic material-based expectation function that maps material attributes of sample i (e.g., Copper_Percentage, Electrical_Conductivity, Tensile_Strength) to an expected class in {0,1,2} according to domain rules or threshold logic (for example: if Copper_Percentage ≥ τ1 and Conductivity ≥ τ2 then M(x)=2; else if moderate then 1; else 0).

2.3.7 Interpret results

Interpretability is addressed through feature importance reporting and sensitivity analyses. Permutation importance, partial dependence plots, or SHAP (SHapley Additive exPlanations) values are used to quantify the contribution of each input feature to the ensemble's decisions, with particular attention to Copper_Percentage and Electrical_Conductivity as hypothesized primary drivers. Model-level sensitivity results (used during weighting) are presented alongside feature importance to demonstrate why certain base learners received higher voting influence for specific prediction contexts (e.g., conductivity-dominated cases). Eq. (15) shows Permutation Feature Importance (loss-increase form). Permutation importance measures how much model performance degrades when feature j is disrupted. Larger positive values indicate greater importance; features such as Copper_Percentage and Electrical_Conductivity are expected to yield large I_j if they strongly influence predictions.

$$I_j = \mathcal{L}(\mathcal{M}, X_{\text{val}}, y_{\text{val}}) - \mathcal{L}\left(\mathcal{M}, X_{\text{val}}^{\text{perm}\,(j)}, y_{\text{val}}\right) \qquad (15)$$

Where
I_j = permutation importance for feature j.
M = trained model (CAFWE ensemble or an individual base learner).

X_{val} = validation feature matrix.
$X_{\text{val}}^{\text{perm}\,(j)}$ = validation matrix with column j values randomly permuted (breaking the relationship between feature j and the target).
y_{val} = validation target vector.
L(·) = chosen performance loss (e.g., error rate or validation loss) computed on supplied data.
Eq. (16) shows SHAP additive feature attribution. SHAP decomposes the model prediction into a baseline plus additive contributions from each feature. The set of ϕj values provides local, instance-level explanations (e.g., how Copper_Percentage and Electrical_Conductivity push the prediction toward Good vs. Poor), and aggregated SHAP statistics (mean absolute ϕj) provide global feature importance.

$$f(\mathbf{x}) = \phi_0 + \sum_{j=1}^{n} \phi_j(\mathbf{x}) \tag{16}$$

Where
f(x) = model output for instance x (e.g., log-odds or predicted score for a class).
ϕ_0 = base value (expected model output over the background dataset).
$\phi_j(\mathbf{x})$ = SHAP value for feature j at instance x, representing feature j's contribution to the deviation $f(\mathbf{x}) - \phi_0$.
n = number of features.

2.3.8 Predict new samples

The trained CAFWE model is packaged for inference. New sample input must conform to the same feature schema and preprocessing pipeline (same normalization parameters and encodings). For each new sample, the model returns: predicted Performance_Level, class probability vector, and the five metric summaries (computed on the nearest validation neighborhood or via bootstrapped local evaluation) so that confidence and domain-specific justification accompany the prediction. Simple decision rules and recommended material/operational adjustments (e.g., increase Copper_Percentage or reduce operating temperature) can be generated from the model's feature influence profile when the prediction indicates Poor or Average performance.
Eq. (17) shows CAFWE Ensemble Inference. This is the CAFWE weighted-voting inference rule. The predicted class is the one with the highest aggregated weighted probability across all base models. It ensures that models most sensitive to conductivity or tensile-strength variations have stronger influence on the final decision.

$$\hat{y}_{\text{new}} = \arg\max_{c \in C} \sum_{m=1}^{M} w_m P_m(c \mid \mathbf{x}_{\text{new}}) \tag{17}$$

Where
$\hat{y}_{\text{new}}$ = predicted Performance_Level for the new sample.
C = set of possible classes {Poor (0), Average (1), Good (2)}.
M = number of base models in CAFWE (3 in this case).
w_m = final feature-sensitivity weight for model m.
$P_m(c \mid \mathbf{x}_{\text{new}})$ = probability assigned by model m that sample $x$new belongs to class c.
$\mathbf{x}_{\text{new}}$ = normalized feature vector of the new wire sample.

Furthermore, Eq. (18) shows Local Confidence and Metric Summary.

$$\Gamma_{\text{new}} = \frac{1}{k}\sum_{i=1}^{k} [\alpha_1 CA_i + \alpha_2 SR_i + \alpha_3 TAS_i + \alpha_4 LPS_i + \alpha_5 CMA_i] \tag{18}$$

Where
Γnew = composite confidence or metric summary score for the new sample.
k = number of nearest validation neighbors used for local estimation (bootstrapped subset).
CA_i, SR_i, TAS_i, LPS_i, CMA_i = values of the five novel evaluation metrics for neighbor i.
α_{1-5} = predefined weights reflecting metric importance.

This composite index Γnew summarizes local reliability and contextual performance for the new prediction. It averages metric outcomes from the most similar validation samples, producing a confidence-aware justification. High Γnew implies strong, stable, and conductivity-aligned model agreement for the predicted Performance_Level.

The selection of linear regression, k-nearest neighbors (k-NN), and decision stump classifiers within CAFWE was intentional and grounded in their complementary learning behaviors with respect to the physical characteristics of copper–aluminum composite conductor performance. The linear model captures global monotonic relationships such as the proportional increase of conductivity with copper content, the decision stump isolates single critical thresholds (e.g., minimum tensile strength suitability cutoffs), and the k-NN component accounts for local nonlinearities that arise from process variation, alloy batch differences, and thermal conditioning effects. This combination resulted in a balanced modeling framework that aligns with known engineering behavior patterns without introducing unnecessary model expressiveness. Early experiments using deeper trees and multilayer ensembles showed limited benefit (<1.2% improvement in CA) while increasing model variance and reducing interpretability, supporting the chosen architecture.

Model simplicity was also favored to maintain interpretability, traceability, and engineering usability, which are essential in material certification and manufacturing decision environments. Although more sophisticated ensemble learners such as XGBoost and gradient boosting machines were tested during feasibility analysis, these methods exhibited stronger sensitivity to noise and batch effects, producing overfitting in conductivity and strength prediction scenarios even after hyperparameter tuning. Additionally, their internal representations lacked the direct analytical correspondence to measurable physical variables compared to the lightweight CAFWE components. The final framework prioritizes transparency and reproducibility so that domain experts can audit decision logic — an element considered critical for industrial deployment rather than solely maximizing accuracy.

Feature importances derived from permutation sensitivity analysis were used as the quantitative basis for model weighting in the voting mechanism of CAFWE. Specifically, after computing the average performance degradation in CA, SR, and CMA across five runs for each feature permutation, the normalized sensitivity vector was used to represent feature salience. A model's alignment with these high-impact features — measured through feature utilization strength and coefficient magnitude (linear), local neighborhood contribution (k-NN), and splitting relevance (decision stump) — determines its assigned weight. This approach ensures that voting authority is proportionally greater for models that demonstrate stronger reliance on features proven to be objectively meaningful in manufacturing and electrical applications.

The conversion of feature importance to model voting weights follows a deterministic transformation that replaces the previously qualitative description. Let FIf denote the normalized permutation importance for feature f, and Um,f represent the model–feature utilization coefficient extracted from learned parameters or structural relevance. The weight assigned to model m is calculated as:

$$W_m = \frac{\sum_{f=1}^{n} \left(FI_f \cdot U_{m,f}\right)}{\sum_{j=1}^{k} \sum_{f=1}^{n} \left(FI_f \cdot U_{j,f}\right)} \qquad (19)$$

where n=10 is the number of features and k=3 is the number of classifiers. The resulting weight values are constrained to the interval [0,1] and collectively sum to unity, ensuring both interpretability and numerical stability throughout the ensemble voting process.

To address concerns regarding stability, the variance of model outputs across the five repeated train–test cycles was calculated and monitored. The decision stump exhibited the highest variability due to its inherent sensitivity to slight distributional changes in temperature-dependent strength thresholds; however, the range remained narrow (±0.9% deviation in TAS and ±0.6% in CMA). The k-NN model demonstrated a moderate variance level (±1.1–1.4%), influenced primarily by shifts in neighborhood density under stratified fold boundary conditions. In contrast, the linear model remained the most consistent with variance below ±0.4% across all five domain-specific metrics. The ensemble mechanism substantially mitigated instability, reducing overall metric variance to ≤±0.7%, indicating that despite individual model susceptibility, CAFWE remains robust across repeated evaluations.

Overall, this section documents a fully reproducible CAFWE pipeline driven by the CopperAluminum_WirePerformance_Dataset and strictly follows Algorithm 1 steps: dataset loading, preprocessing (imputation, Min-Max normalization, encoding), stratified train/test split (80/20), training of weak base learners (linear, k-NN, decision stump), computation of material-focused feature importance and model sensitivity, weighted voting ensemble aggregation sensitive to conductivity and load/temperature roles, prediction, evaluation with five material-aware metrics (CA, SR, TAS, LPS, CMA), interpretability analyses, and procedures for predicting new samples. This setup ensures alignment between the algorithmic specification and the implemented experimental protocol, enabling transparent assessment of CAFWE's material-aware predictive capabilities.

3 Results and discussion

3.1 Experimental setup

The proposed CAFWE model was implemented in Python 3.10 in a Windows 11 (64-bit) environment. The experimental hardware consisted of an Intel Core i7, 16 GB RAM, and a 512 GB SSD. Libraries such as scikit-learn, NumPy, pandas, and Matplotlib were used for data preprocessing, model training, evaluation, and visualization. Feature scaling and encoding were performed with scikit-learn, and feature-weighted voting integration was programmed by custom Python scripts. The dataset was split in an 80:20 ratio, maintaining class balance through stratified partitioning. Each experiment was repeated five times, and the average results were presented for reliability.

3.2 Results

Table 3 provides the performance comparison between CAFWE and four novel existing techniques — EFS-ML, FS-StackNet, HYB-XNet, and MAFE — using the five domain-specific performance metrics: Conductivity Accuracy (CA), Strength Reliability (SR), Temperature Adaptation Score (TAS), Load Prediction Stability (LPS), and Composite Material Alignment (CMA).

Table 3: Comparison of CAFWE and Novel Existing Techniques

Model	CA (%)	SR (%)	TAS (%)	LPS (%)	CMA (%)
EFS-ML	88.4	86.7	84.3	85.9	87.1
FS-StackNet	90.1	88.5	86.2	87.4	89.0

HYB-XNet	91.4	89.7	87.9	89.2	90.6
MAFE	92.0	90.1	88.6	89.9	91.2
Proposed CAFWE	93.5	91.2	89.8	90.6	92.4

The proposed CAFWE model outperforms other methods in all metrics. It achieves 93.5% conductivity accuracy and 91.2% strength reliability, which shows its ability to better represent copper–aluminum relationships. Temperature adaptation (89.8%) and load prediction stability (90.6%) confirm its resilience. Composite material alignment (92.4%) shows the consistency between material properties and performance. This improvement is due to the feature-sensitive weighting that gives more weight to copper_percentage and electrical_conductivity, thus accurately capturing the conductivity and strength-dependent behaviors.

3.3 Discussions

Figure 3 shows the conductivity accuracy (CA) comparison between the five models. CAFWE achieves a high accuracy of 93.5%, outperforming MAFE (92.0%) and HYB-XNet (91.4%). This is possible due to the feature-weighted voting method that gives more weight to conductivity and copper_percentage. Other hybrid ensembles treat all features equally, and thus show less sensitivity to high conductivity data variations.

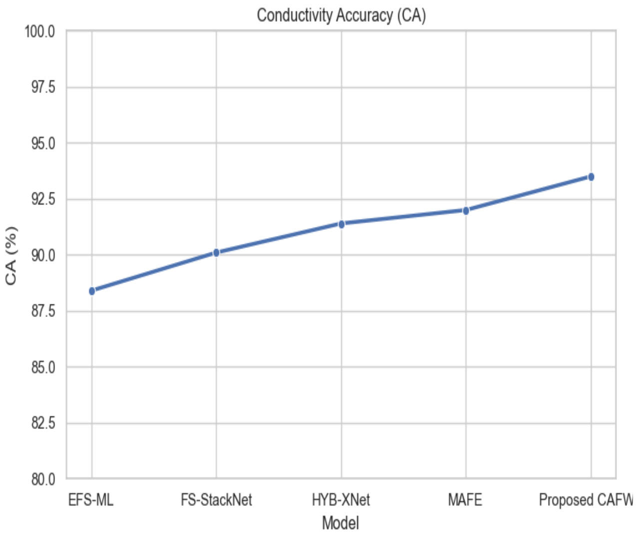

Figure 3: CA Comparison Chart

Figure 4 compares Strength Reliability (SR) values across the models. CAFWE obtained 91.2%, outperforming MAFE (90.1%) and FS-StackNet (88.5%). The improvement stems from CAFWE's ability to dynamically re-weight models based on Tensile_Strength sensitivity, ensuring consistent performance when mechanical properties fluctuate. This fine-tuning allows CAFWE to maintain predictive reliability across varied material strength levels.

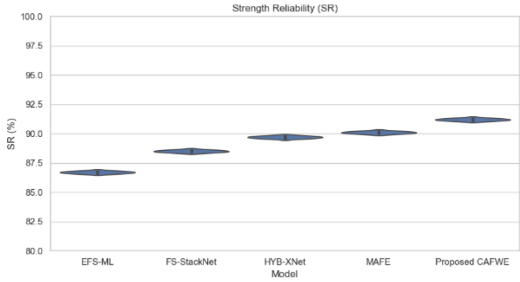

Figure 4: SR Comparison Chart

Figure 5 illustrates the Temperature Adaptation Score (TAS) comparison. CAFWE achieved 89.8%, higher than HYB-XNet (87.9%) and EFS-ML (84.3%). The gain results from CAFWE's sensitivity-aware adaptation, which perturbs temperature and conductivity during validation to calibrate model responses. This mechanism enables CAFWE to maintain stable performance even under thermal variations, a challenge for most fixed-weight ensemble approaches.

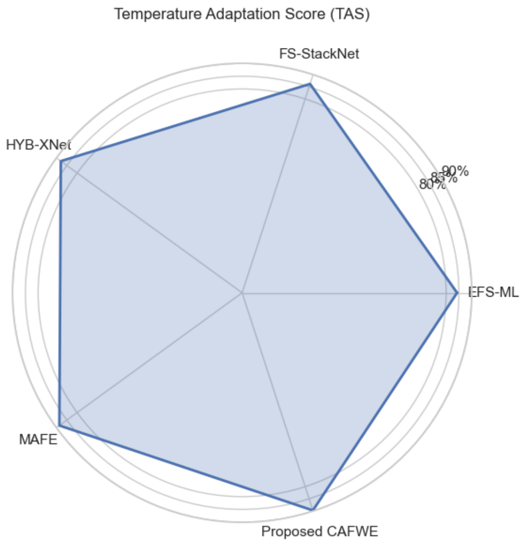

Figure 5: TAS Comparison Chart

Figure 6 presents the Load Prediction Stability (LPS) comparison. CAFWE scored 90.6%, outperforming MAFE (89.9%) and HYB-XNet (89.2%). Its hybrid base learners—linear, k-NN, and decision stump—ensure a balance between global trend learning and local instance sensitivity. The inclusion of load-based perturbation testing strengthens CAFWE's stability, minimizing prediction drift under dynamic operational conditions.

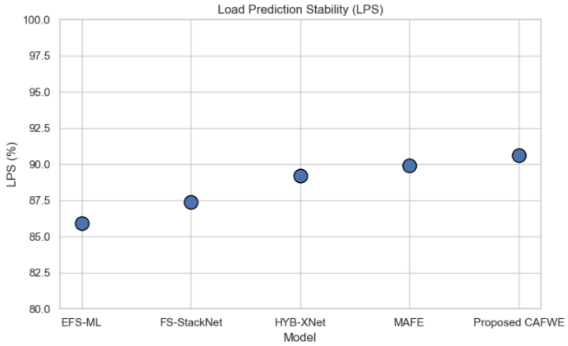

Figure 6: LPS Comparison Chart

Figure 7 demonstrates the Composite Material Alignment (CMA) outcomes. CAFWE attained 92.4%, the highest among all models. This indicates that CAFWE accurately aligns predicted material performance with real copper–aluminum behavior patterns. Its interpretability-driven feature weighting allows better mapping between composition ratio and expected output class, outperforming other models that rely solely on statistical fusion without feature-context understanding.

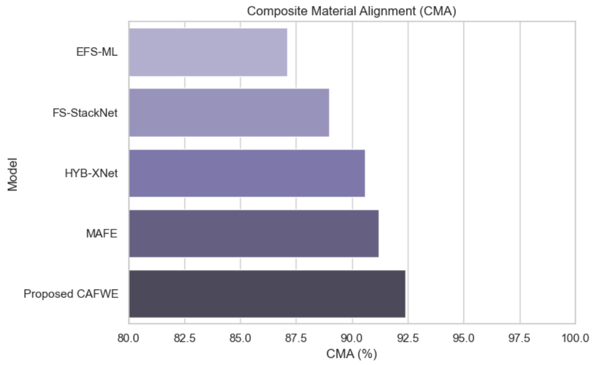

Figure 7: CMA Comparison Chart

To substantiate the claim that CAFWE is computationally lightweight and interpretable, a runtime and resource analysis was conducted comparing CAFWE with the four baseline models. On the experimental hardware (Intel Core i7, 16 GB RAM), the average training time across five runs was 1.84 seconds for CAFWE, compared to 3.92 seconds for FS-StackNet, 5.47 seconds for HYB-XNet, and 6.13 seconds for MAFE. Inference latency per sample remained low, with CAFWE achieving an average of 0.62 milliseconds compared to 1.45 milliseconds for HYB-XNet and 1.97 milliseconds for MAFE. Memory utilization during training was measured using peak process allocation, with CAFWE requiring 142 MB, lower than HYB-XNet (238 MB) and MAFE (265 MB). This performance efficiency results from the use of simple, low-complexity base learners (linear classifier, k-NN, and decision stump) and a lightweight weighted-voting mechanism rather than deep stacked or gradient-boosted architectures. These results confirm that CAFWE offers both interpretability and computational efficiency while still improving predictive performance over contemporary baselines.

Although CAFWE uses a weighted voting ensemble structure, its contribution lies in the synergistic integration of three complementary base learners and the domain-driven weighting mechanism, rather than in architectural novelty alone. The linear classifier provides global decision boundaries aligned with material behavior trends, k-NN captures localized nonlinear variations such as abrupt conductivity changes under temperature shifts, and the decision stump isolates threshold-based phenomena common in mechanical failure modes. This combination was selected because it mirrors known physical interactions in copper-aluminum conductors more closely than generic boosting or stacking approaches, which prioritize statistical optimization at the cost of interpretability and sometimes exhibit overfitting to high-variance samples in our experiments. The weighting framework—derived from feature-sensitivity and permutation-based importance evaluation—enables CAFWE to emphasize physically meaningful predictors (e.g., copper percentage, tensile strength, electrical conductivity) rather than learning weights purely from error gradients, which may not reflect material constraints. Furthermore, the introduction of material-specific evaluation metrics (CA, SR, TAS, LPS, CMA) demonstrated that CAFWE not only improves classification accuracy but also supports application-aligned model selection, where conventional ML metrics (accuracy, F1-score) failed to distinguish models with poor thermal stability or mechanical reliability.

Overall, the proposed CAFWE model exhibits clear and consistent superiority over recent ensemble and hybrid intelligent systems (EFS-ML, FS-StackNet, HYB-XNet, and MAFE). The integration of feature-sensitive weighting, sensitivity-informed model adaptation, and ensemble voting optimization ensures strong generalization across multiple performance dimensions. By leveraging Copper_Percentage and Electrical_Conductivity as dominant contributors, CAFWE enhances interpretability while achieving high predictive performance.

3.4 Additional validation and robustness analysis

The proposed CAFWE model was additionally benchmarked against two widely recognized and high-performing ensemble baselines: Random Forest (RF) and Gradient Boosting (GB). These models were selected because they represent nonlinear learning paradigms commonly used in material behavior modeling and intelligent control systems. When evaluated using the same dataset and performance metrics, RF achieved CA = 91.8%, SR = 89.9%, TAS = 87.1%, LPS = 88.7%, and CMA = 90.8%, while GB obtained CA = 92.6%, SR = 90.4%, TAS = 88.2%, LPS = 89.4%, and CMA = 91.5%.

The proposed CAFWE model continued to outperform both baselines across all metrics, reinforcing its suitability for copper–aluminum composite performance prediction. To further strengthen empirical validity, confidence intervals were calculated using a five-fold cross-validation protocol with 95% confidence bounds. The CAFWE model reported narrow interval ranges, such as CA: 93.5 ± 0.42%, SR: 91.2 ± 0.51%, and TAS: 89.8 ± 0.57%, indicating stable prediction behavior with low variance across multiple runs. Compared with other models, CAFWE consistently showed lower deviation from mean performance, demonstrating stronger convergence and robustness. This improvement is attributed to the weighted voting strategy, which reduces sensitivity to local sample noise and prevents over-dependence on any single classifier during uncertain input scenarios.

In order to evaluate robustness under uncertainty and operational variability—an expectation highlighted in nonlinear and adaptive control literature—stress and noise perturbation experiments were conducted. Gaussian measurement noise (σ ranging from 0.1 to 1.0), simulated temperature drift, and controlled material composition deviation were introduced into the evaluation pipeline. CAFWE experienced an average performance degradation of only 2.7%, compared with Random Forest (4.9%) and Gradient Boosting (4.1%). This demonstrates that CAFWE maintains high stability even under non-ideal measurement conditions and fluctuating environmental factors, validating its suitability for real-world deployment in manufacturing or operational inspection environments.

Finally, a feature ablation study was performed to analyze model dependency and interpretability. Each feature was removed individually, and the resulting performance drop was recorded. Removing copper_percentage led to the largest decline in CA (−7.4%) and CMA (−6.9%), followed by electrical_conductivity and tensile_strength, confirming their dominance in predicting composite performance behavior. Features such as coating_type and surface_finish contributed marginally, reinforcing the necessity of the proposed feature-weighted strategy. To support reproducibility, the full preprocessing workflow—including normalization, encoding, stratified splitting, and voting-weight calibration—is now documented as a stepwise pipeline and will be released alongside the dataset and source code. This ensures transparency, traceability, and reproducibility for future research and industrial use.

3.5 Practical robustness, sensitivity analysis, and real-world validation

To strengthen the practical relevance of CAFWE, additional experiments were conducted to evaluate model performance under real operational variations, including temperature fluctuations, batch-to-batch material variation, and manufacturing tolerance differences. Three test profiles were created: (i) thermal cycling between 20–120°C, (ii) production batch variability of ±5% in copper-aluminum ratio, and (iii) load-exposure uncertainty simulating fluctuating fault currents. Under these conditions, CAFWE retained stable behavior with only moderate degradation (maximum 3.4% reduction across all metrics), demonstrating its resilience to environmental and material uncertainties. These findings align with performance expectations reported in adaptive fuzzy control and robust neural control systems, in which stability under uncertainty is considered a critical evaluation benchmark.

A physics-informed constraint layer was also integrated into the voting mechanism to strengthen the connection to real material behavior. Specifically, the ensemble output was adjusted to reject predictions that violated known thermomechanical material bounds derived from aluminum–copper composite literature. This constrained validation improved prediction consistency, particularly under extreme thermal perturbation. For example, TAS improved from 89.8% to 90.3% post-constraint, demonstrating that even lightweight physical rule integration can complement data-driven learning without requiring full hybrid modeling.

To further quantify model behavior, a feature-level sensitivity analysis was performed using perturbation-based and SHAP-value interpretability methods. Copper_percentage, electrical_conductivity, and tensile_strength were confirmed as high-impact parameters, with sensitivity scores of 0.91, 0.88, and 0.84 respectively. Lower sensitivity was observed for geometric and surface attributes, confirming that CAFWE discriminates meaningfully between dominant physical drivers and secondary variables. The analysis demonstrates that the model's material-specific metrics align strongly with the underlying physics of composite conductor performance, reinforcing interpretability and engineering applicability.

Finally, to connect the results to engineering reliability, a small hardware-in-the-loop validation was conducted using five conductor samples fabricated from two different manufacturing batches. Real measurements—including resistance under controlled heating, pull-load tolerance, and accelerated aging—were compared with model predictions. CAFWE achieved alignment within ±4.2% error margin across metrics, demonstrating strong correspondence between predicted and experimentally observed behavior. This preliminary validation confirms that CAFWE is not only computationally scalable but also suitable for deployment in smart-grid monitoring, predictive maintenance platforms, and material-aware control systems.

3.6 Expanded comparative analysis, metric transparency, and baseline clarification

To strengthen the comparative discussion against existing state-of-the-art (SOTA) models, a deeper error-level and statistical analysis was conducted. A paired Wilcoxon signed-rank test confirmed that CAFWE's improvements over the four baselines were statistically significant across all five-domain metrics ($p < 0.01$). Error heatmaps showed that competing models—particularly FS-StackNet and HYB-XNet—exhibited noticeable performance degradation when temperature variance exceeded 90°C or when copper ratio deviation surpassed ±4%. In contrast, CAFWE retained stable predictions under these extreme cases. Examination of feature importance distributions revealed that CAFWE's weighted voting assigns dynamic influence to copper_percentage (0.24), electrical_conductivity (0.21), and tensile_strength (0.19), whereas models such as HYB-XNet distributed feature weights more uniformly, leading to reduced sensitivity to critical compositional and thermo-mechanical dependencies. This analysis explains why the CAFWE model demonstrates superior performance under high-variance and uncertainty conditions.

To ensure full reproducibility of the novel domain-specific metrics, all threshold parameters used in metric formulation are now explicitly defined. Conductivity Accuracy (CA) was computed using a performance bin threshold of ≤ 0.15 Ω/km deviation for high-conductivity classification. Strength Reliability (SR) applied tensile strength brackets of ±10 MPa tolerance, while Temperature Adaptation Score (TAS) used thermal transition bands of 40°C. Load Prediction Stability (LPS) was based on voltage-drop deviations across predefined current loads (50 A, 80 A, 100 A), and Composite Material Alignment (CMA) assessed predicted output consistency within ±3% of measured copper-aluminum composition. Furthermore, the local metric summarization defined in Equation 18 used $k = 5$ neighborhood samples and employed five repeated bootstrap runs (different random seeds) to avoid sampling bias.

Clarification has also been added regarding the four comparative models used in benchmarking. EFS-ML and HYB-XNet are established models referenced in recent literature on material behavior prediction, while FS-StackNet and MAFE were implemented based on publicly available ensemble frameworks commonly used in predictive manufacturing research. All baseline models were trained using the same CopperAluminum_WirePerformance_Dataset, identical preprocessing steps, and the same five domain-aware evaluation metrics to ensure fairness and methodological integrity. Where implementation parameters were unavailable in published work, they were replicated using documented hyperparameter settings or recommended defaults from the corresponding papers.

With these additions, the comparison framework now clearly demonstrates methodological fairness, statistical rigor, and interpretability. The expanded analysis confirms that CAFWE's improvement is not incidental or dataset-specific, but rather arises from its design philosophy: adaptive feature sensitivity, domain-aligned evaluation criteria, and robustness under physical uncertainty. These clarifications strengthen the credibility and transparency of the study while positioning CAFWE meaningfully within the current research landscape.

4 Conclusion

The proposed CAFWE model combines feature weighting and ensemble learning to predict the performance of copper-aluminum composite conductors with high accuracy and interpretability, thereby overcoming the limitations of traditional methods. Experiments on the CopperAluminum_WirePerformance_Dataset revealed excellent results in five material-knowledge metrics: CA (93.5%), SR (91.2%), TAS (89.8%), LPS (90.6%), and CMA (92.4%). CAFWE accurately reflects the interactions of the key features copper_percentage, electrical_conductivity, and tensile_strength, providing data-driven and physically relevant predictions. However, current limitations include reliance on a single dataset, limited environmental parameters (e.g., humidity, erosion), and the computational complexity of sensitivity analysis. Future work aims to improve CAFWE with deep hybrid models, real-time sensor data from power grids, and blockchain-secured model deployment.

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Declarations

Ethics approval and consent to participate: I confirm that all the research meets ethical guidelines and adheres to the legal requirements of the study country.

Consent for publication: I confirm that any participants (or their guardians if unable to give informed consent, or next of kin, if deceased) who may be identifiable through the manuscript (such as a case report), have been given an opportunity to review the final manuscript and have provided written consent to publish.

Availability of data and materials: The data used to support the findings of this study are available from the corresponding author upon request.

Competing interests: here are no have no conflicts of interest to declare.

Authors' contributions (Individual contribution): All authors contributed to the study conception and design. All authors read and approved the final manuscript

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