Mechanics of Advanced Composite Structures Vol (Year), Serial Number, First page – Last page

Mechanics of Advanced Composite Structures

Semnan University

Journal homepage: https://macs.semnan.ac.ir/

ISSN: 2423-7043

Research Article

Hybrid Polymer Composite Tensile Strength Estimation using K-Nearest Neighboring Classification Algorithm

Vijaykumar S Jatti [a*], Neeta Deshpande [b], Saiyathibrahim A[c], Balaji K [d]

[a] *Department of Mechanical Engineering, School of Engineering and Applied Sciences, Bennett University, Greater Noida, UP, India.*
[b] *R.H. SAPAT College of Engineering, Management Studies and Research, Maharashtra, India.*
[c] *University Centre for Research and Development, Chandigarh University, Punjab, India.*
[d] *Department of Aeronautical Engineering, Parul Institute of Engineering and Technology, Parul University, India*

ARTICLE INFO

Article history:

Received: 2023-10-19
Revised: 2024-03-22
Accepted: 2024-05-12

Keywords:

Acrylonitrile Butadiene Styrene ;
Copper;
k-nearest neighbour ;
Surfactant;

ABSTRACT

The aim of this research work is to characterize the tensile strength of ABS-Cu and ABS-Al composites of different proportions of percentage compositions, as well as the incorporation of surfactant material. For the analysis carried out in the present study, the k-Nearest Neighboring (kNN) classification algorithm is used in order to predict the tensile strength of the various compositions of the ABS-Al and ABS-Cu composites. Real data was not used to train the model due to the time-consuming process; instead, they resorted to synthetic data for the classification model, and for the tensile strength data, they were trained and predicted with better results. The kNN classification algorithm of the ABS-Cu predicted the k-value accuracy to be 80% for k=1 and k=2, and 85% for k=3 and k=5. Similarly, the prediction accuracy for the ABS-Al composition yielded the same results: As the value of k is increased, the required percentage of samples is 80% for k=1 and k=2, 85% for k=3, and 90% for k=5, respectively. The kNN classification algorithm model was also successful in predicting tensile strength, with a recall of more than 80% and an F1 score of 90-95%. A higher quantity of copper and aluminium is said to have the ability to improve the tensile strength of the specimens.

1. Introduction

Sophisticated production materials are essential in today's manufacturing environment to sustain a competitive advantage for companies in the global arena. Polymer matrix composites, more particularly, have emerged as the most favoured materials compared to metals and alloys because of their enhanced characteristics [1]. Specific interest is drawn to the Acrylonitrile Butadiene Styrene (ABS) composites enhanced with copper and aluminium particles due to their improved mechanical properties. These composites have quite a large prospect for different industrial uses where strength and durability are required [2]. Another important factor is the ingredient known as surfactants, which enable enhanced distribution of metal particles in the polymer matrix and thus affect the mechanical characteristics of the final material [3]. Earlier literature suggests that composites containing ABS bring about property

*** Corresponding author.**
E-mail address: arobalaji@gmail.com

Cite this article as:
Vijaykumar S Jatti ,Neeta Deshpande , A. Saiyathibrahim and K. Balaji ., 2025. Hybrid Polymer Composite Tensile Strength Estimation using K-Nearest Neighboring Classification Algorithm. *Mechanics of Advanced Composite Structures*, 12(1), pp. xx-xx
https://doi.org/10.22075/MACS.2024.39315.2050

improvements. Different researchers have employed some of the machine learning methods in the exploration of predicting various properties of these polymer composites. Gong et al. (2022) discussed the improvement of the mechanical properties of ABS products using a combined technology of Additive Manufacturing (AM) and Injection Molding (IM). Results from the experiment showed that samples with a hybrid microstructure were stronger than parts that were made of only AM, and the strongest samples were almost as strong as IM parts [4]. The blend of ABS and organically modified montmorillonite nano clay was studied by Shishavan et al. (2014), where the compatibilizer used was polymethylmethacrylate (PMMA). They studied the relationship between nanoclay content, melt temperature, holding pressure, and time in tensile strength and hardness using Taguchi experiments. These findings show that the addition of PMMA has a pronounced effect on the dispersion of nanoclay and the fluidity of the material, with 2% of nanoclay providing the maximum tensile strength and hardness of 4% [5]. Mohammed et al. (2023) investigated and concluded that SVM, DT, RF, kNN, and ANN are from the viewpoint of the accuracy of SVM for the prediction of the tribological properties of the UHMWPE/SiC composites [6]. Esmaeili and Rizvi (2023) proved that ensemble learning models are better than ANNs at predicting stress-strain curves of polymer composites [7]. Jain et al. (2024) used the tribological properties of MWCNT-reinforced PMMA nanocomposites and found that the GBM predictions were most accurate [8]. Kurt and Oduncuoglu (2015) used applied load, sliding speed, composite reinforcement type, and weight percentage to create an ANN for modelling the dry sliding wear behaviour of ultrahigh molecular weight polyethylene composites. A model was developed that was able to accurately predict the volume loss, with the two most critical influencing factors for the wear profile determined to be the applied load and the sliding speed [9]. Aliyu et al. (2019) applied the Taguchi method for the improvement of tribological features of UHMWPE nanocomposites containing SiC nanopowder. Optimization tests predicted in ANOVA and regression models the level of process parameters where friction and specific wear rate were at their minimums; these values were proved by means of validation tests [10]. Abdellah et al. (2018) studied the impact of Short Basalt Fiber (SBF) on the ABS polymer composites and their characteristics produced through the injection molding process. Characterization data established that tensile strength was enhanced up to 5 wt% SBF, while the reduction in area was reduced with up to 2wt% SBF; investigations showed that hardness was enhanced at higher loading of SBF. The impact strength reduced in general while wear resistance increased with higher SBF content [11]. Bulanda et al. (2023) investigated the application of PC/ABS polymer composites in, for instance, 3D printing through melted extrusion modelling. A silica-alumina, bentonite modified with quaternary ammonium salt, and a combination of lignin and silicon dioxide were incorporated into the matrix. According to the obtained results, it was established that the modification of fillers had a considerable impact on the processing and functional characteristics of the composites [12]. Amena et al. (2022) synthesize chemically modified spent coffee husk with high-density polyethylene materials with enhanced mechanical characteristics for industrial use [13]. Raza et al. (2020) also researched the development of thermally reduced graphene oxide/ABS composites and discovered that the inclusion of 0.2wt% graphene oxide provided better tensile properties than that of graphite, which, however, reduced as the filler content increased. Another research study shows that the use of this two-step mixing method led to an enhancement of the dope dispersion of the graphene oxide in the ABS matrix [14]. Rasana et al. (2021) studied the preparation of thermally reduced graphene oxide/ABC composites; the result observed that the tensile properties were increased by adding 0.2wt% graphene oxide compared to graphite, although the composite property is decreased when the filler amount is increased. Graphene oxide also increased the glass transition temperature of ABS with no effect on thermal stability [15]. Triantou et al. (2019) examined the effects of graphene on ABS/polycarbonate (PC) and ABS/polypropylene (PP) blends, reporting that graphene reduced the melt flow index and affected thermal degradation but improved the Young's modulus, particularly in ABS/PP blends [16]. Joynal Abedin et al. (2021) found that incorporating graphene oxide and maleated styrene-ethylene/butylene-styrene (SEBS-g-MAH) into ABS/talc composites significantly enhanced their tensile, flexural, and modulus properties while maintaining comparable impact strength to pure ABS. The additives also improved thermal stability and interfacial adhesion, making the composites more suitable for various applications [17]. Jatti et al. (2024) investigated the impact of copper powder on the wear properties of ABS-Cu composites. They determined that wear loss decreased with a composition of 23% ABS, 70% Cu, and 7% surfactant. Machine learning models described the wear behaviour well and showed that the invention may be used to create more suitable composite materials for particular wear behaviours in industrial applications [18].

A vast number of prior works have considered the mechanical properties of ABS-based composites, but relatively few works have considered machine learning approaches for predicting the properties as a function of the composition. [19-24]. The increased awareness of the devastating effects of synthetically developed materials on nature has resulted in the development of eco-friendly and sustainable materials [25-30]. Despite a large body of work on the mechanical properties of ABS composites, mainly tensile strength, very little work exists as a predictive model for understanding the effect of changing the composition of filler material (copper and aluminium) on the tensile strength of these composites. Furthermore, studies based on real-world experimental data tend to be slow and resource-intensive efforts. This research gap is to be addressed by utilizing synthetic data that can potentially be used to train the KNN model more quickly at a lower cost with equally good predictions. This study uniquely addresses the research gap in predictive modeling by exploring how variations in filler material composition, specifically copper and aluminium, influence the tensile strength of ABS composites. By employing synthetic data to train a K-Nearest Neighbors (KNN) model, the study offers a faster and more cost-effective alternative to traditional methods that rely on real-world experimental data. This approach not only enhances the efficiency of material property prediction but also provides valuable insights into optimizing composite formulations without the need for extensive and costly experimental procedures.

This research aimed to characterize the tensile strength of ABS-Cu and ABS-Al composites with varying proportions and surfactant material while employing the kNN classification algorithm to predict tensile strength. Addressing a gap in predictive modeling, the study explored how changes in filler material composition (copper and aluminium) influence the mechanical properties of ABS composites. By utilizing synthetic data, the research sought to train the kNN model more quickly and cost-effectively than relying on real-world experimental data. The study aimed to enhance material properties by accurately estimating tensile strength through machine learning and surfactant use, ultimately contributing to academic literature and supporting the future large-scale production of high-performance ABS-metal composites.

Using machine learning to estimate the tensile strength of the developed ABS-Cu and ABS-Al composites and the use of surfactants, this work provides a multifaceted interdisciplinary solution to improving the properties of the materials. The goal of this study is to find out the tensile strength of ABS-Cu and ABS-Al composite materials that have different amounts of copper and aluminium in them, as well as to see how adding a surfactant material makes them stronger. Specifically, the purpose of this study is to predict their tensile strength via the k-nearest neighbor classification algorithm. This new body of research has the objective of enriching the academic and scientific literature and being useful for future large-scale production.

2. Materials and Methods

2.1. Materials Used

The production of high-performance material ABS-metal composites is attributed to the use of ABS, Cu, Al, and surfactant materials. The choice of source and characteristics directly impacts the quality and functionality of the final composite. Specific weight percentages of ABS, metallic powders (99.9% pure), and surfactant (noninphinoethoxylate) are utilized for each primary substance, as detailed in Tables 1 & 2. In this case, the total material weight is assumed to be 250 grams. The weight percentage of copper must be maintained with a minimum variation of 20% to ensure accurate molding and improve the mechanical properties of the composite. Surfactants reduce surface tension and prevent agglomeration, enhancing the dispersion of metal particles within the ABS matrix. By forming a compatible interface, they promote adhesion between the matrix and fillers, improving stress transmission and the overall performance of the composite. The outcomes are better mechanical qualities and a more uniform distribution.

2.2. Fabrication of Composites

ABS was obtained from Sigma-Aldrich, a leading supplier of high-quality industrial ABS. This material has a density of approximately 1.04 g/cm^3, a tensile strength of approximately 40 MPa, and excellent impact resistance, ductility, and toughness. It can be processed at temperatures up to 240°C. Sigma-Aldrich also provided pure copper powder with a density of 8.96 g/cm^3. Copper is ideal for conductive composites due to its high electrical conductivity and low thermal conductivity, with a tensile strength of about 210 MPa. Aluminium powder, obtained from Sigma-Aldrich, has a density of 2.70 g/cm^3, a thermal conductivity of ~237 W/m·K, and a tensile strength of about 90 MPa. A non-ionic surfactant was acquired from Sigma-Aldrich to enhance the mechanical and thermal properties of the composite by promoting the dispersion of metal particles within the polymer matrix. The surfactant's compatibility with both the metal particles and ABS ensures strong interfacial bonding, a key factor in its selection. To assess the impact of metal composite materials on mechanical properties, four distinct compositions of the primary material and metallic powder were prepared based on weight percentages. A surfactant was included to enhance covalent bonding and flowability between the ABS and the metallic powders, specifically copper and aluminium. Copper and aluminium powders served as reinforcement materials in this study. Figures 1(a) and (b) illustrate the ABS-Cu and ABS-Al composites, respectively. The copper and aluminium powders, sourced from the market, had a particle size of approximately 50 µm. Specific percentages by weight of each main material, metallic powders, and the surfactant were utilized to achieve optimal mechanical properties concerning the strength of the composite material. In this study, a total material weight of 250 grams was considered 100%. To obtain accurate and optimal results in molding and enhancing the mechanical properties of the composite material, the percentage by weight of copper must be maintained with at least a 20% difference. A vertical hand-operated injection molding machine, as shown in Figure 1 (c), was used to fabricate the metallic composites. In the present study, ABS-Cu composites comprised 65% ABS, 30% copper, and 5% surfactant; 44% ABS, 50% copper, and 6% surfactant; and 23% ABS, 70% copper, and 7% surfactant. Similarly, ABS-Al composites included 65% ABS, 30% aluminium, and 5% surfactant; 44% ABS, 50% aluminium, and 6% surfactant; and 23% ABS, 70% aluminium, and 7% surfactant. Figure 2 displays the integrated experimental and machine learning framework for material analysis.

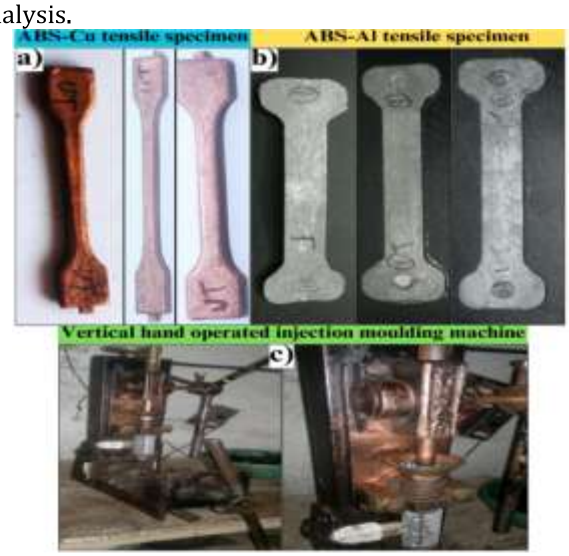

Fig. 1. (a) ABS-Cu tensile specimen, (b) ABS-Al tensile specimen, and (c) Vertical hand-operated injection moulding machine

2.3. Testing Method

This study's use of synthetic data facilitated a more comprehensive exploration of the research subject and enabled the development and validation of models under various scenarios, without the need for an impractically large amount of real experimental data. When obtaining sufficient real data proved challenging or costly, synthetic data production was employed to complement or substitute for the real experimental data. To establish variability in the data, the original data was contaminated with allowed random Gaussian noise, thus producing synthetic but realistic data. The data was created using MATLAB code in which controlled random noise was added to the original data. The synthetic data introduces the variability through this controlled noise to reflect the variability obtained in authentic experimental data. This approach made it possible to conduct empirical and theoretical tests and validation of models or theories within environments that are carefully controlled [31]. The synthetic data was produced with the help of a data perturbation technique that shifts the privacy of some individuals in the dataset and, thus, maintains the dataset's usefulness for analyses. This data was therefore produced by making slight modifications to the numbers to be close to the actual experimental data, all with the aid of a MATLAB program, meaning the synthetically generated data was almost similar to the actual experimental data since tiny changes were made in the decimal places of the data. The repeatability test was conducted on three samples. The ABS-Cu composites' tensile strength measurements had a standard deviation of 2.35, which is about 6.3% of the mean value of 37.2434. This is just about adequate for research purposes. Although it reduces variability in its performance, for mass production or critical applications, the need to reduce this variability is important to get more consistent performance. Because of the higher variability present in the data, a standard deviation of 4.72 for the ABS-Al composite, that is, approximately 29.6 percent of the mean tensile strength, would also be acceptable for research purposes. This variability should be reduced, as with the ABS-Cu composite, for more consistent and reliable material properties in mass production or high-stakes applications. Coded as 1 were the tensile strength values greater than the mean, while those below the tensile strength average were coded as 0. In this study, synthetic data generation is carried out via a perturbation-based method that can be implemented via MATLAB code, which can be found on MATLAB File Exchange using GitHub. This approach makes use of fixed parameters and algorithms, sometimes with, sometimes without, seeding random numbers so that they always produce the same results when the program is run. A deterministic setup ensures reproducible and controlled experiments by producing the same result on each program execution. The perturbation approach aims to introduce random noise or variations to the sample, simulating a different experiment with slight variability [32]. From here, this process starts with a base dataset, which can be a minimal set of real data or a set imagined with given constants. Thereafter, noise is used within some range by altering the main parameters involved in the process; the material, pressure, or temperature is changed to let some noise in. This continues in a way that produces a set of n synthetic data points that covers an additional area of the experimental space. It is crucial to use this approach in order to extend the possibilities of the study and analyze the circumstances that cannot be met in real life; however, it would allow us to test the models and conclusions produced. It shall be noted that synthetic data generation has its limitations, which lie in the fact that generating real-world data, particularly for the generation of natural language text or images, becomes highly complex and requires more complicated techniques. However, synthetic data generative models often concentrate on common trends and patterns, ignoring nuances or anomalies that likely exist in the real data. Lastly, if the synthetic data is not appropriately secured, there is a risk of inadvertently revealing private or sensitive information, as the synthetic data is usually created on top of real-world datasets. However, to overcome these limitations, generators are expected to generate data with diversity and variety so that the data resembles the real-world complexities. To keep them current with real-world data, this study monitored and updated synthetic datasets.

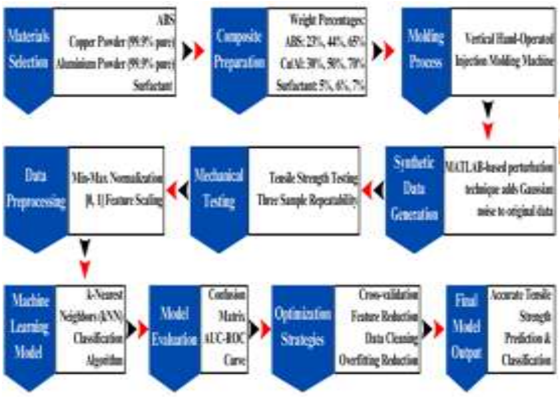

Fig.2. Flowchart outlining the experimental methodology

3. Machine Learning

In this work, the kNN classification algorithm was used to evaluate various material compositions and perform tensile tests on the prepared samples. Based on experimental data, synthetic data were produced utilizing a data generation algorithm in MATLAB to perform a deeper analysis of tensile strength via classification. For better analysis, confusion matrices and the AUC-ROC graphs were also plotted. Classification is a type of supervised machine learning algorithm in which the program learns from certain datasets or observations in order to assign new observations into well-defined classes or groups. In this study, any tensile strength value greater than the average was classified as 1, and any value below the average received a classification of 0, essentially splitting the sample data into two.

Here, the kNN classification algorithm was used; the method calculates the distances of the average tensile strength value to each of the samples. This algorithm incorporates several hyperparameters [33]:

1. The number of neighbors, by which the quantity of the nearest neighbors used for classification of each point from the target data set is defined.
2. The distance measure serves as the distance metric for determining the distance between two points.
3. Distance weight that is specified by equality or by inverse, that is, distances between a pair of object points and the center point are either equal or inversely ratioed?
4. The study examines hyperparameter tuning and distance metrics in the k-Nearest Neighbors (kNN) algorithm for classifying ABS-Cu and ABS-Al composites. Using cross-validation to balance bias and variance, the study tested k values of 1, 2, 3, and 5, finding that higher k values improved accuracy. For the ABS-Cu composite, accuracies were 80% for k = 1 and 2, 85% for k = 3, and 90% for k = 5, with a similar trend for ABS-Al. The study employed Euclidean distance as the distance metric, using cross-validation to minimize validation error. Ultimately, the optimal configuration for the kNN model was k = 5 with Euclidean distance, achieving the highest classification accuracy for both composites.

The results of the confusion matrix in predicting the model were obtained with the help of the metrics module from the sklearn library in Python. In order to make accurate predictions, the dataset was partitioned into 80% training and 20% testing. The confusion matrix provides information about the true positive (TP), true negatives (TN), false positives (FP), and false negatives (FN) values, which give correct and incorrect predictions. In this study, k values of 1, 2, 3, and 5 were used to acquire a variety of classification results, and the AUC-ROC curve was used for measurement. The AUC score for the model is higher than 0.5, which means it has good performance as it can distinguish between the classes depending on feature distance.

For estimating tensile strength in hybrid polymer composite data, the kNN classification algorithm was used because this algorithm is very sensitive to complex and subtle local structures [34]. The kNN classification algorithm is therefore useful in predicting tensile strength since it avails itself of how local areas in the distribution of the independent variables affect tensile strength. This capability is more relevant to hybrid polymer composites since their mechanical properties may be highly sensitive to localized influences from the constituents. For these reasons, the kNN classification algorithm is also ideal when model interpretability and usability are paramount. In tensile strength estimation, it provides a robust, non-parametric approach that works well with a range of data sources without the need for much parameter fine-tuning. This is advantageous because the relationship that exists in between the input features and the output may be intricate in some ways. Lastly, the tensile strength in hybrid polymer composites tends to be governed by non-linear synergistic, antagonistic, or additive components. Especially when the data set size is small to medium, which is frequently the case when conducting material science research, this kind of model is ideal for capturing such non-linear relationships. The algorithm is thus ideal for estimating tensile strength in hybrid polymer composites because its operation does not depend on the availability of a preconceived model of the local details [35].

This makes it a good fit for studying such properties, as their relations are often non-linear and coupled. Moreover, the kNN classification algorithm structure tied to simple majority voting among surrounding start points also shields it from over-learning, provided it is well calibrated (for example, by defining the right value for variable k). This research aimed at improving the kNN classification algorithm in order to decrease instances of overfitting in the system as well as to provide the model with additional strengths. For the elements, as it was mentioned before, the choice of the value of k in the optimization function was tuned through the process of cross-validation, which allows minimizing both bias and variance. Feature normalization attempted to contribute the same degree of importance to the distance metric, while dimensionality reduction also helped combat and rectify the problem of the curse of dimensionality. Those areas include data cleaning, whereby noise and outliers are removed in order to improve the overall distance calculations. And for the ridge, they increased training data exposure so it generalized well with unseen data. Such collective endeavors proposed earlier have involved the pursuit of further refinements to the kNN model in terms of accuracy, stability, and the model's capacity to generalize to new data. It has some limitations notwithstanding; its computational cost poses a possibility to limit the tensile strength dataset because each new data point has to be assigned a distance to all other data points. Additionally, the distances computed in this method are sensitive to noise or irrelevant features in the data, which can undermine the distance calculations and accurate prediction thereof. Although for many applications, Random Forest and Support Vector Machines, or any other model from the area of supervised learning, would be the best choice. The kNN classification algorithm can be superior in certain conditions; for instance, if the dimensionality of the data is low, simplicity of the model is preferred, and computational speed is not decisive. However, by removing the overfitting problem using different methods such as cross-validation, normalization of features, reductions of dimensions, and data preprocessing, kNN can cycle with fairly high efficiency and high stability, which makes the kNN classification algorithm a reasonable selection in some cases. In light of these considerations, this research chose to implement the kNN model.

In this study, the normalization technique, Min-Max scaling, was selected as part of the preprocessing step in order to solve the problem of feature scaling that is well known to affect the kNN classification algorithm. This process scales and translates all the features to the range of [0, 1] so that all features are given equal importance for the distance calculations. The normalization formula used is given in equation (1):

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

Where X_{max} and X_{min} refer to the maximum and minimum range and values of a feature, respectively. This helps avoid a situation where one feature controls the distance measurement, since features are usually measured on different scales, improving the efficiency of the kNN model and ensuring stable and reliable results for different data distributions. This study used MATLAB to generate synthetic data by adding random Gaussian noise to the original dataset, aiming to introduce variability that mimics real-world experimental conditions. However, this method has limitations, including oversimplification of complex data distributions, omission of critical anomalies and nuances, potential privacy risks, and bias in model training, which may impair the generalizability of the findings to real-world data. To address these issues, the researchers should conduct comparative analyses of the distributions of synthetic and real data using statistical tests or visualizations, discuss the potential biases introduced by the Gaussian noise in their kNN classification results, explore more advanced data generation techniques to better capture the representation of the data, and perform sensitivity analysis to evaluate model performance across different synthetic data distributions and noise levels, thereby enhancing the robustness of their overall approach.

4. Results and Discussion

The ABS polymer matrix provides the fundamental framework and adaptability for the composite. ABS is renowned for its good ductility and toughness, helping to prevent abrupt fracture by enabling the composite to absorb and disperse energy under tensile stress. As the ABS content decreases, the composite becomes less ductile but more rigid. Conversely, a higher ABS content often increases the ductility and hardness of the composite. The surfactant aids in the uniform dispersion of copper particles throughout the ABS matrix, ensuring an even distribution of loads when the composite experiences tensile stress. Proper application of the surfactant improves dispersion and strengthens interfacial bonding, resulting in increased tensile strength [36]. Copper used in this composite serves as reinforcement, dramatically improving the mechanical properties due to its inherent strength and stiffness. The result revealed that ABS-Cu composition with ABS of 65.05% and Cu 30% and with 5% surfactant material, provided the highest tensile strength of 41.057 N/mm^2 (Figure 2(a)). This result shows clearly that tensile strength declines as the percentage composition of copper rises above this exact element. In general, the incorporation of copper particles increases the benefit of extra load capacity under tensile stress. Increased levels of copper can increase the tensile strength of the composite, although if the copper levels are too high, this can cause problems of poor matrix distribution and a weakened interfacial bonding to reduce the tensile strength [37]. This tends to agree with the finding highlighted above that more emphasis needs to be laid on determining the right proportion of the ABS polymer, copper reinforcement, and surfactant to obtain the right tensile properties of the polymer composite. It is noted that improving the uniform dispersion of reinforcement materials, such as copper and aluminium, in the ABS matrix significantly enhances tensile strength. Noninphinoethoxylate, the surfactant, ensures the uniform dispersion of these particles, thereby distributing the load evenly under tensile stress. This process keeps the particles from sticking together badly and making the composites less strong. Additionally, it improves the bonding at the point where the ABS polymer meets the metal particles. This makes it easier to control the transfer of stress and makes the composite less likely to deform. In addition, the surfactant enhances the material integrity of the whole by enhancing the homogeneity of the mixture, thereby enhancing tensile strength. Consequently, stronger, more durable composites capable of handling higher mechanical loads in various mechanical applications are obtained. The ABS-Al composite containing 64.85% ABS, 30.10% Al, and 4.92% surfactant material possessed the highest tensile strength of 27.95 N/mm^2. This shows that the tensile strength is reducing as the percentage of aluminium in the polymer matrix increases. The composite's reinforcing phase, which is constituted by aluminium particles, gives the composite material higher levels of strength and stiffness. Aluminium improves the composite's ability to carry increased tensile loads due to a better strength-to-weight ratio. As indicated in the previous sections, the degree of aluminium dispersion and concentration also determines the total tensile strength. Typically, composites with a higher aluminium content are stronger, but an excessive aluminium concentration without a balanced matrix material can lead to brittleness [38]. The hybrid polymer composites containing copper as the reinforcement exhibited higher tensile strength compared to those with aluminium reinforcement.

The heatmap illustrates the correlation between the percentage compositions of ABS, copper, and surfactant material and their impact on the tensile strength of the ABS-Cu composite (Figure 3(a)). The analysis indicates that the ABS composition has a significant effect on tensile strength, while the influence of the surfactant material (noninphinoethoxylate) is relatively minor, as confirmed by the F-test (Figure 3(b)). In contrast, for the ABS-Al composition, the surfactant material has a substantial impact on tensile strength, followed by the percentages of ABS and copper, as shown in the F-test results and heatmap correlation matrices in Figures 4(a) and 4(b). The surfactant has a relatively minor impact on the tensile strength of pure ABS. However, its influence becomes substantially more significant in ABS-aluminium and ABS-copper composites. This is likely due to the surfactant's ability to modify the interaction between the polymer matrix and the metal particles, facilitating enhanced dispersion, adhesion, and overall material integrity. In the ABS-Al and ABS-Copper compositions, the surfactant aids in achieving more homogeneous mixtures, which directly contributes to improved mechanical properties, including tensile strength. This assertion is supported by the statistical significance observed in the relevant analyses, such as the F-test and heatmap correlation matrices. The kNN regression models for various values of 'k' demonstrated greater accuracy compared to other classification models, such as the support vector classifier, decision tree classifier, and logistic regression. Therefore, the kNN classification algorithm model was chosen as the preferred method.

ABS-Cu and ABS-Al composites offer improved tensile strength and rigidity compared to pure ABS. Figure 5 shows the results of the tensile test on different ABS-Cu compositions: (a) ABS 65% + copper 60%, (b) ABS 44% + copper 50%, and (c) ABS 23% + copper 70%. Similarly, Figure 6 shows the results of the tensile test on different ABS-Al compositions: (a) ABS 65% + aluminium 30%, (b) ABS 44% + aluminium 50%, and (c) ABS 23% + aluminium 70%. These composites provide better thermal management due to the metallic fillers. ABS-Cu, in particular, adds electrical conductivity, which can be useful for certain electronic applications. However, production is more expensive due to the cost of metal fillers and additional processing requirements.

Non-metallic fillers, that is, non-metal fillers, also reduce the weight of the composite compared to metal-filled composites. However, environmental interaction may lead to the oxidation of metals, compromising the long-term stability of the structure [39]. In total, both ABS-Cu and ABS-Al composites exhibit better mechanical and thermal properties than the base polymer, although they are more expensive, and the Cu-filled material is vulnerable to corrosion. This reduced the bias of the model for the kNN classification algorithm, especially due to its sensitivity to training data sets, which increased the reliability when identifying the performance of the models using K-Fold Cross-Validation. In this approach, the model was trained and validated based on a different split of the data for each fold, whereas in the previous approach, the data was split into an equal number of folds [40, 41]. This method was more informative than the previous one because it presented the model accuracy on the different test data sets, which trained the model with different test divisions as compared to the train-test division.

4.1. Hyperparameter Tuning

Some of the parameters included are k, the number of nearest neighbours to include in the final model; the distance function; and the function used to weight the nearest neighbours' points. The number k of neighbours is crucial—if set too small, the model becomes overly sensitive to noise; if set too large, the model may overlook important patterns. The graph plots the accuracy or error rate of the model against the different k components of cross-validation to select the perfect k [42]. The implementation of the selected distance function, which increases with dimensionality, is also a crucial consideration. Different metrics are tried, and cross-validation is used to find out which one of them gives the least validation error. Moreover, the kNN classification algorithm permits a degree of flexibility in neighbour contribution, where higher degrees of distance are likely to have a minor influence from the neighbouring samples. The ability of cross-validation can also be employed in order to compare the impacts of the distance-based weighting scheme and the uniform weighting scheme on the model.

4.2. Mitigating Overfitting

Nonetheless, there are different measures taken in the kNN classification algorithm in order to reduce the issue of overfitting. First, choosing the variable k is crucial, as a higher k value reduces variance and overfitting but simultaneously increases bias if set at $k > 1$. Furthermore, feature scaling is crucial because the kNN classification algorithm depends on the scaling of the features; standardizing or normalizing all the features will minimize the likelihood of overfitting because one feature will not dominate the distance measurements. Last, regarding the high dimensionality of data, to reduce this course, which is likely to cause overfitting, Principal Component Analysis (PCA) or feature selection can be used to limit the overall number of features through which the model tends to focus [43].

4.3. Model Evaluation Metrics

While measuring the accuracy of a model to solve classification problems, it is crucial to not only use the basic evaluation criteria, such as precision rate, recall rate, or F1 rate, but also to use a confusion matrix in order to recognize the kind of mistakes that a model makes during classification. It does so in a way that yields more subtle information than simply the measure of accuracy. When it comes to two-class classification problems, the ROC curve must be plotted and the AUC calculated as well. The ROC curve specifically tracks the true positive rate compared to the false positive rate for different thresholds of the model, thereby improving its comprehension of the model's ability to classify between two classes [44].

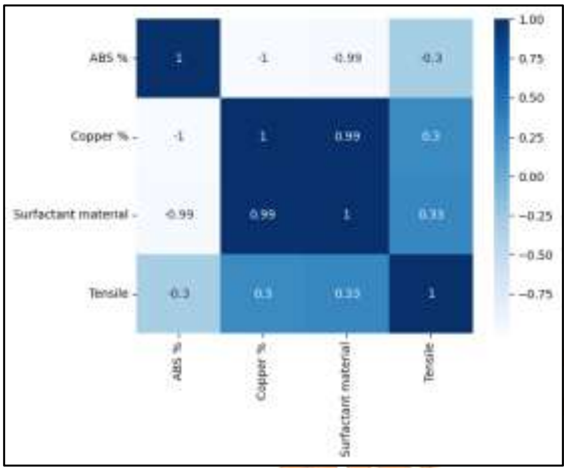

Fig.3. (a) ABS-Cu composition heatmap

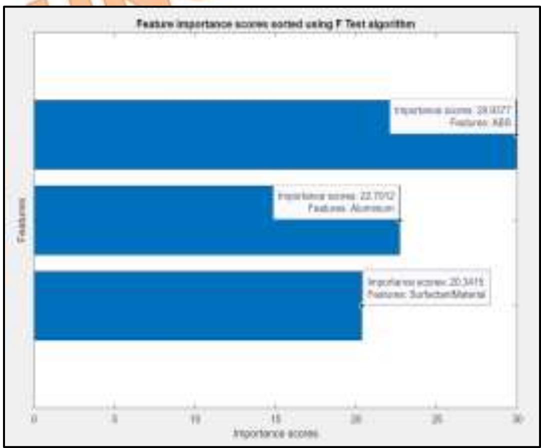

Fig.3. (b) F-test for ABS-Cu selection

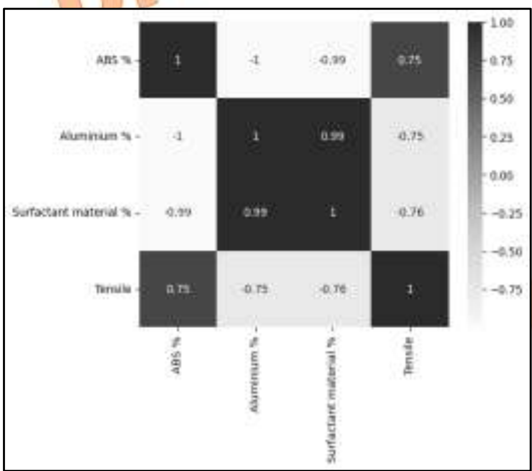

Fig. 4. (a) ABS-Al composition heatmap

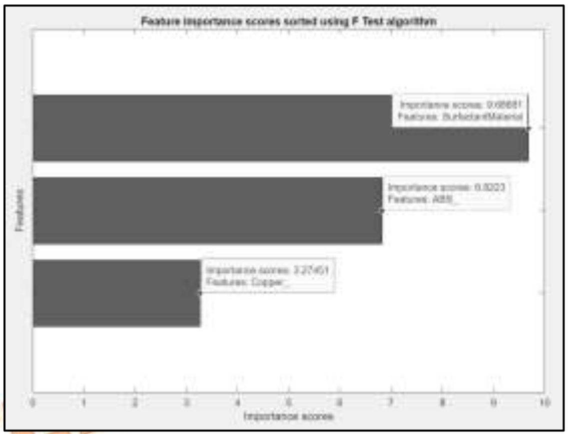

Fig.4 .(b) F-test for ABS-Al selection

Fig. 5. (a) ABS-Cu (65% ABS + 60% Copper) after the tensile test, (b) ABS-Cu (44% ABS + 50% Copper) after the tensile test, and (c) ABS-Cu (23% ABS + 70% Copper) after the tensile test

Fig. 6. (a) ABS-Al (65% ABS + 30% aluminium) after the tensile test, (b) ABS-Al (44% ABS + 50% aluminium) after the tensile test, and (c) ABS-Al (23% ABS + 70% aluminium) after the tensile test

4.4. Classification of Machine Learning: ABS-Cu

In this study, the kNN classification algorithm was employed to predict the tensile strength of the ABS-Cu composite material, demonstrating promising results with varying values of k. The kNN classification algorithm model achieved accuracies of 80%, 80%, 85%, and 90% for k values of 1, 2, 3, and 5, respectively, as shown in Figures 6(a)-(d). These conclusions indicate that the quality of the model increases with the number of neighbors, adding to the attraction of smoother and more generalized approximations [45]. The kNN classification algorithm involves finding the length of the straight line between a given test data point and its neighbors in the data set, and classifying any given test data point to the tensile strength category by finding the mean of the nearest neighbor's tensile strength. To identify the classification boundary for this system, the average tensile strength of the ABS-Cu composition was defined to be 37.01 N/mm^2; any composition that had a tensile strength above this value was assigned a value of true positive (indicated as 1); any composition below this value was assigned a value of true negatives (indicated as 0). The classification of each prediction is evaluated using a confusion matrix, which helps identify the four possible outcomes: FN (false negatives) are in the bottom-left quadrant, TP (true positives) are in the bottom-right quadrant, TN (true negatives) are in the top-left quadrant, and FP (false positives) are in the top-right quadrant. The aforementioned confusion matrix analysis demonstrates the model's overall comprehension, particularly in predicting the classification categories of the collected products. A model with a reasonably adequate predictive power is evident from the confusion matrix of the ABS-Cu composite with a 'k' value of 1, shown in Figure 7 (a). It demonstrates high accuracy in correctly classifying instances as both "True" (TP: 7) and "False" (TN: 9). However, the model exhibits some misclassification with a few instances incorrectly predicted as "True" when they were actually "False" (FP: 1) and vice versa (FN: 3). Considering the confusion matrix, the best model with the k value of 2 has a very high accuracy (Figure 7 (b)). It does so with rather excellent accuracy, as evidenced by the high TP and TN values above.

Notably, there are no false positives (FP: 0), meaning the model never incorrectly predicted an instance as "True" when it was actually "False". However, there are a few false negatives (FN: 4), indicating that the model misclassified some instances as "False" when they were actually "True". Overall, the model with k = 2 demonstrates a high level of accuracy and a strong ability to correctly classify instances, particularly in avoiding false positives. Based on the confusion matrix, the model with a k value of 3 exhibits a very good performance (Figure 7 (c)). It correctly identifies most of the instances, as indicated by the high TP and TN values. While there are a few misclassifications (FP: 1 and FN: 2), the model demonstrates a strong ability to correctly classify instances. This suggests that a k value of 3 might be a suitable choice for this particular model and dataset, as it balances accuracy with a low number of misclassifications. Based on the confusion matrix, the model with a k value of 5 exhibits excellent performance (Figure 7 (d)). It correctly identifies most of the instances, as indicated by the high TP and TN values. Notably, there are no false positives (FP: 0), meaning the model never incorrectly predicted an instance as "True" when it was actually "False". While there are a few false negatives (FN: 2), indicating that the model misclassified some instances as "False" when they were actually "True", the overall performance is strong. The confusion matrix analysis reveals that the kNN classification algorithm models with k values of 2, 3, and 5 exhibit strong predictive performance for the ABS-Cu composite. The k = 2 model demonstrates excellent accuracy, with high true positive and true negative rates and no false positives. The k = 3 model also shows very good performance, correctly identifying most instances. The k = 5 model exhibits excellent overall performance, with high accuracy and no false positives, though a few false negatives. These results suggest that k values of 2, 3, or 5 may be suitable choices for this dataset, as they provide a balance of high accuracy and low misclassification.

Table 3 shows the classification report where the precision and recall values for tensile strength predictions consistently exceeded 0.80, confirming the model's high degree of accuracy in predictions. Precision shows the share of true positives returned among all positive predictions, while recall describes how precise the model is when it predicts the true positives among all actual positive cases. Both metrics over 0.80 mean a highly effective model, which suppresses false positives and captures most of the true positive cases. This indicator further strengthens its reliability in predicting the tensile strength of the ABS-Cu material as the model's overall accuracy remains consistent at 80% or higher. The tensile strength of the ABS-Cu material was estimated using the model, and its accuracy increased to 80% or more. The performance of the model supports its reliability in the tensile strength of the estimated ABS-Cu material. The AUC-ROC curve of 0.7285 enhances the outlook for the classifier, specifically for the kNN classifier. This performance measure is used in the context of model assessment, where the closer to one is used to imply better diagnosis of a given classification model. An AUC ROC of the value 0.7285 indicates that the kNN classification algorithm model is capable of providing dependable distinction between the true positive and true negative classifications to predict the tensile strength of ABS-Cu. Further shown in Figure 7 (e) is the AUC-ROC worktable, exhibiting a good balance of sensitivity and specificity in the preferred model to give away [46]. Therefore, the kNN classification algorithm in this study showed high and stable predictive accuracy for the predictions of the tensile strength of the ABS-Cu composite material. Network generalization ability is good, and for different k values, the model is stable and reliable. K=5 is the best determination of accuracy, reaching 90% [47]. Therefore, the observed high prediction accuracy with relatively high precision, recall, AUC-ROC, and the confusion comparison attests to the fact that the kNN classification algorithm has correctly captured most of the underlying features of the tensile strength identification in similar composites, thus affording a powerful tool for trending future composite studies.

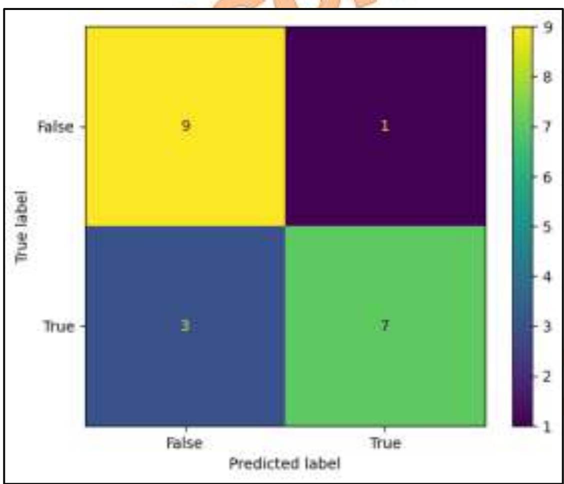

Fig. 7. (a) ABS-Cu confusion matrix for k value of 1

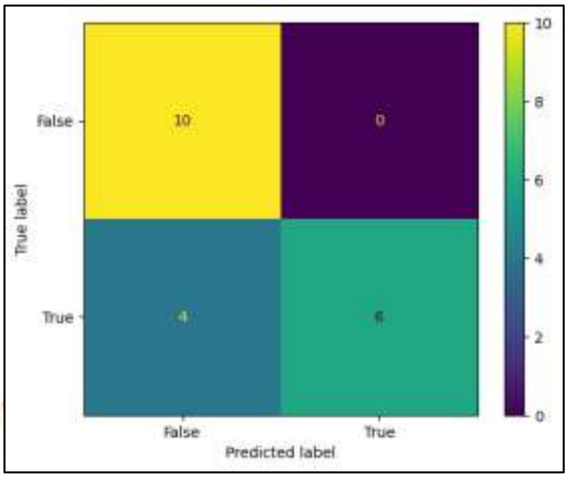

Fig. 7. (b) ABS-Cu confusion matrix for k value of 2

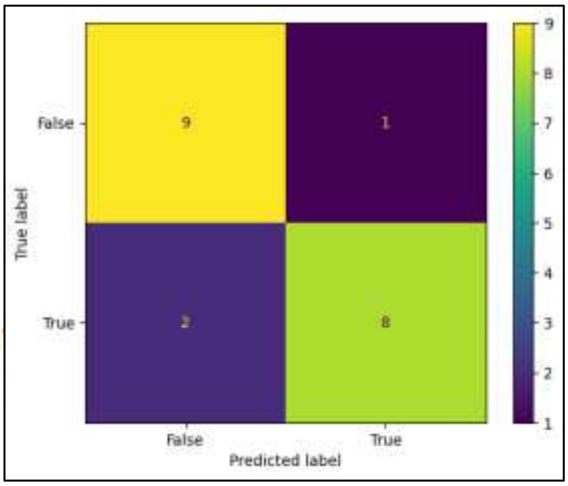

Fig. 7. (c) ABS-Cu confusion matrix for k value of 3

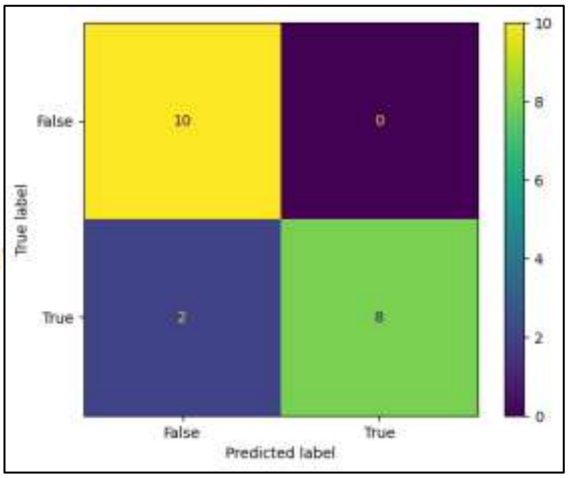

Fig. 7. (d) ABS-Cu confusion matrix for k value of 5

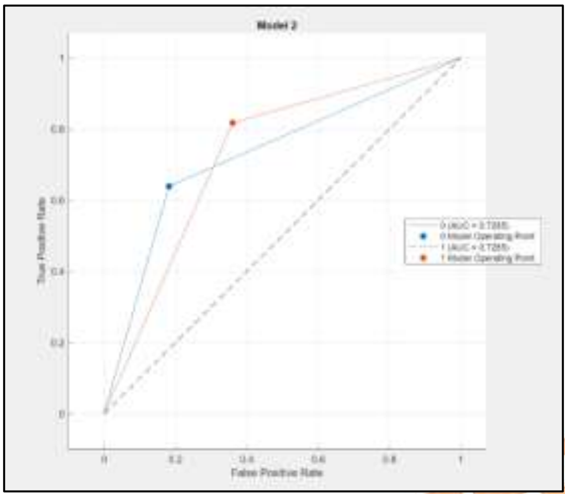

Fig. 7. (e) AUC vs ROC curve for ABS-Cu

4.5. Classification of Machine learning: ABS-Al

The kNN classification algorithm was also employed in this study to predict the tensile strength of the ABS-Al composite material. The k-fold cross-validation results for both the ABS-Cu and ABS-Al models are presented in Figure 8. Similar to the results for the ABS-Cu composition, the kNN classification algorithm model demonstrated promising performance across various values of k, achieving classification accuracies of 80%, 80%, 85%, and 90% for k=1, 2, 3, and 5, respectively, as illustrated in Figures 9 (a)-(d). The confusion matrix for the ABS-Al composite with a k value of 1 demonstrates a relatively satisfactory model performance. The model correctly identifies a majority of instances as both "True" (TP: 7) and "False" (TN: 9), indicating high accuracy (Figure 9 (a)). However, there are instances where the model misclassifies data, with some instances incorrectly predicted as "True" when they were actually "False" (FP: 1) and vice versa (FN: 3). These misclassifications suggest potential areas for improvement through further model tuning and parameter optimization. Based on the confusion matrix, the model with a k value of 2 exhibits excellent performance. It correctly identifies most of the instances, as indicated by the high TP and TN values. Notably, there are no false positives (FP: 0), meaning the model never incorrectly predicted an instance as "True" when it was actually "False". However, there are a few false negatives (FN: 3), indicating that the model misclassified some instances as "False" when they were actually "True" (Figure 8 (b)). Overall, the model with k = 2 demonstrates a high level of accuracy and a strong ability to correctly classify instances, particularly in avoiding false positives. Based on the confusion matrix, the model with a k value of 3 exhibits excellent performance. It correctly identifies most of the instances, as indicated by the high TP and TN values (Figure 8(c)). Notably, there are no false positives (FP: 0), meaning the model never incorrectly predicted an instance as "True" when it was actually "False". While there are a few false negatives (FN: 3), indicating that the model misclassified some instances as "False" when they were actually "True", the overall performance is strong. This suggests that a k value of 3 might be a suitable choice for this particular model and dataset, as it balances accuracy with a low number of misclassifications and demonstrates a high level of reliability in avoiding false positives. Based on the confusion matrix, the model with a k value of 5 exhibits excellent performance. It correctly identifies most of the instances, as indicated by the high TP and TN values. Notably, there are no false positives (FP: 0), meaning the model never incorrectly predicted an instance as "True" when it was actually "False". While there are a few false negatives (FN: 3), indicating that the model misclassified some instances as "False" when they were actually "True", the overall performance is strong (Figure 9(d)). This result suggests that a k value of 5 might be a suitable choice for this particular model and dataset, as it balances accuracy with a low number of misclassifications and demonstrates a high level of reliability in avoiding false positives. The confusion matrix analysis reveals that the kNN models with k values of 2, 3, and 5 exhibit strong predictive performance for the ABS-Al composite.

The k = 2 model is equally accurate, with very high true positive and true negative rates and no false positives. With the k = 3 model, excellent performance with most of the instances being correctly identified without producing any false positives, but a small number of false negatives. For the k = 5 model, the overall performance is high, with accuracy (90%) and zero false positives, but a few false negatives. The results indicate that k values of 2, 3, or 5 might be appropriate choices for this dataset since they produce high accuracy at the lowest misclassification rates. This higher performance with larger k values is probably due to better generalization of the model, which yields less impact from outliers or data noise that would lead to more reliable predictions [48]. The kNN classification algorithm works by computing the Euclidean distance between a test data point and its nearest neighbors. Consequently, it classifies the test data point based on whether its tensile strength is above or below the average tensile strength of its nearest neighbors. For the case of ABS-Al, the classified process was to determine if the tensile strength of a given sample was above or below the tensile strength average. True positives were labelled as the predictions higher than the average tensile strength, and false positives were for predictions below. This binary classification is evaluated through a confusion matrix, which helps identify the four quadrants: true negatives, false negatives, true positives, and false positives. The detailed class report includes all these key evaluation metrics, such as precision, recall, F1 score, and support, as shown in Table 4. For the tensile strength predictions for the ABS-Al composition, the precision and recall values were both very high, greater than 0.80, which indicates that the model is very good at flagging true positives and not flagging false positives. Precision refers to the ratio of correctly predicted positives to total predicted positives, and recall represents the percentage of positives that the model accurately identifies. These metrics suggest that the kNN model is both accurate and can be relied upon to predict the tensile strength of the ABS-Al composite. Moreover, a further confirmation of the balanced performance of the model is also proven by the F1 score, which combines precision and recall in a single measure [49]. It can be concluded that the ABS-Al composition exhibits good model performance with the AUC-ROC value of 0.8662. The AUC-ROC curve is also important when comparing the accuracy of a classifier; the closer to 1 the value of AUC-ROC, the higher the classifier's diagnostic accuracy. This value tells that the model is capable of distinguishing between positive and negative true outcomes. The AUC-ROC value, which is highly significant as depicted in Figure 9 (e), strengthens the comprehension of a high level of confidence in the tensile strength of ABS-Al as predicted by the kNN classifier. Consequently, the kNN classification algorithm tested consistently and predictably high-performance rates in estimating the tensile strength of the ABS-Al composite. Both data sets yield a high accuracy rate of up to 90% at k = 5, which shows that the prediction quality of the model is quite good, as evident from the high values of precision = 0.93, recall = 0.92, and F1 score = 0.92. The following AUC-ROC value, equal to 0.8662, supports the fact that the model is of high accuracy and can predict the tensile strength in the composition of ABS-Al. These results described here show that the kNN classification algorithm is promising for predicting the tensile strength of composite materials and may be applied to other material science investigations where similar phenomena are observed.

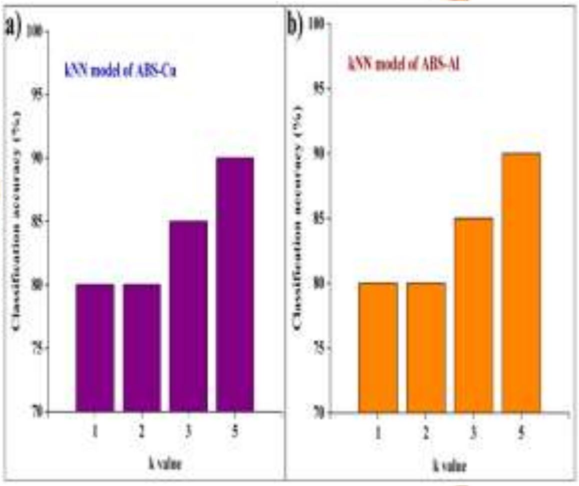

Fig. 8. k-fold cross-validation (a) ABS-Cu and (b) ABS-Al

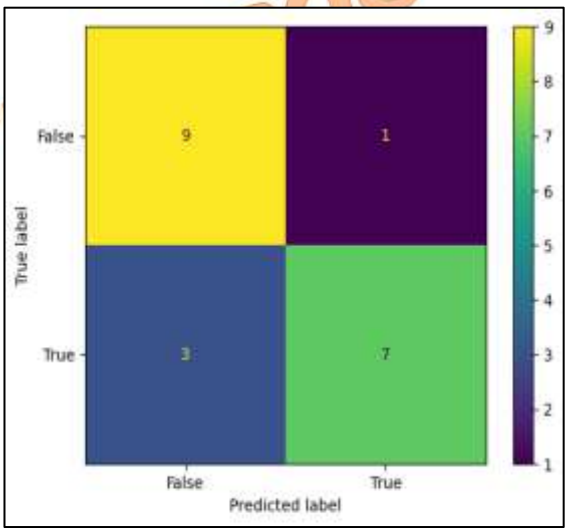

Fig. 9. (a) ABS-Al confusion matrix for k value of 1

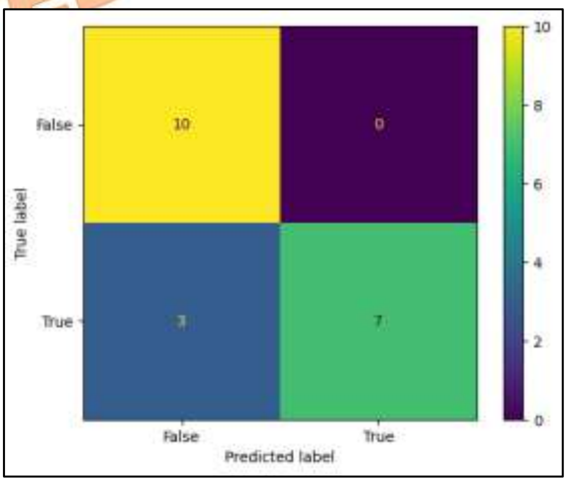

Fig. 9. (b) ABS-Al confusion matrix for k value of 2

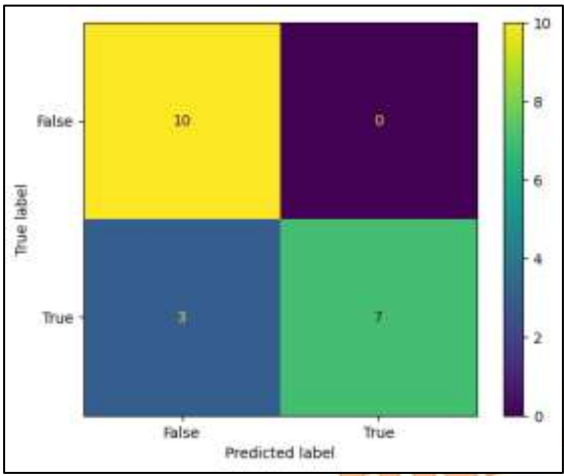

Fig. 9. (c) ABS-Al confusion matrix for k=3

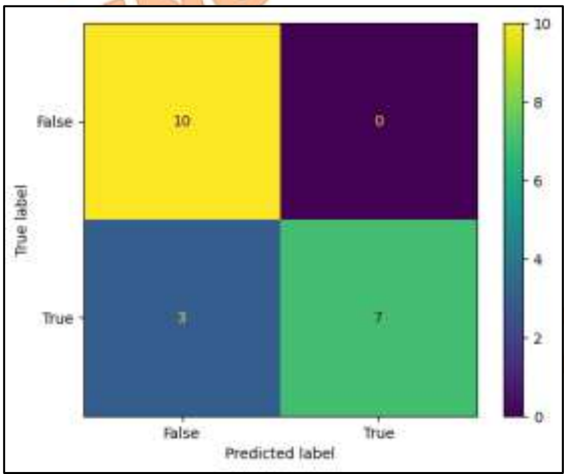

Fig. 9. (d) ABS-Al confusion matrix for k=5

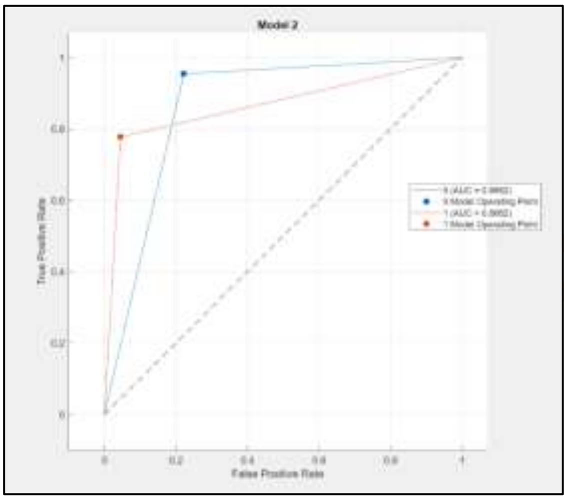

Fig.9. (e) AUC vs ROC curve for ABS-Al

4.6. Microstructural observation

In this section, the microstructural features of the ABS-Cu and ABS-Al composites were analyzed using SEM for the optimized parameters. In the case of the ABS-Cu composite, the optimized combination identified is 65.05% ABS+30% Cu+5% surfactant material. In the case of the ABS-Al composite, the optimized combination identified is 64.85% ABS+30.10% Al+4.92% surfactant material. SEM analysis of injection-molded ABS-Cu composite shows that Cu particles aid efficient stress transfer and help improve the load-bearing capacity, leading to optimum tensile strength (Figure 10 (a)). Furthermore, the design of the clean particle-matrix interface also facilitates effective stress transmission and reduces the chance of debonding or voids that may lead to the weakening of the composite. Nevertheless, ABS matrix cellular morphology characterized by indications of crystallization has a two-sided effect: it enhances stiffness, but at the cost of ductility and tensile strength. The composite in this way presents impressive tensile strength, but more evaluations of the matrix morphology dependence are necessary. Once the optimal copper particle content in the ABS matrix is exceeded, the tensile strength can be diminished for a variety of reasons. At higher Cu particle concentrations, Cu particles can agglomerate, which disrupts the Cu dispersion and also results in localized stress concentrations that weaken the composite. Moreover, the excess Cu content decreases the load-bearing capacity of the ABS matrix, resulting in a loss of structural integrity. Further, particle packing is greater, leading to poor interfacial bonding between the particle and matrix, resulting in voids or debonding in the composite and thus weakening it. Moreover, while Cu particles strengthen the composites, this also enhances brittleness, reducing the capability of the matrix to take in energy and, therefore, making it more likely to crack or fracture in the development and thus decreasing the overall strength in tension. In the same way, an SEM analysis of the injected ABS–Al composite shows that the Al particles are evenly distributed within the ABS matrix (Figure 10 (b)). This makes the load-bearing capacity and stress transfer higher, which means that the composite has a high tensile strength. The absence of a clean particle-matrix interface also indicates minimal voids or debonding and enables stress transfer. The cellular morphology of the ABS matrix (spherulitic growth) is characterized by mixed influence, as it can enhance stiffness but does decrease ductility and reduce the overall tensile strength. Several factors exist that can diminish the tensile strength when increasing the aluminium particle content of the ABS matrix above an optimal level. Agglomeration of particles at higher concentrations causes disruption in the homogeneous particle distribution to localize stress concentrations in the composite, reducing the strength of the material. Furthermore, with excessive Al loading, the loading continuity and load-bearing capacity of the ABS matrix can be reduced, and consequently, the overall tensile strength of the composite can decline. Additionally, increased particle addition can cause bonding issues at the particle–matrix interface, resulting in voids or debonding. In addition, because additional Al content helps increase the stiffness of the composite, there is a risk of severely reducing the tensile strength such that the composite is prone to cracking and failure under tensile stress.

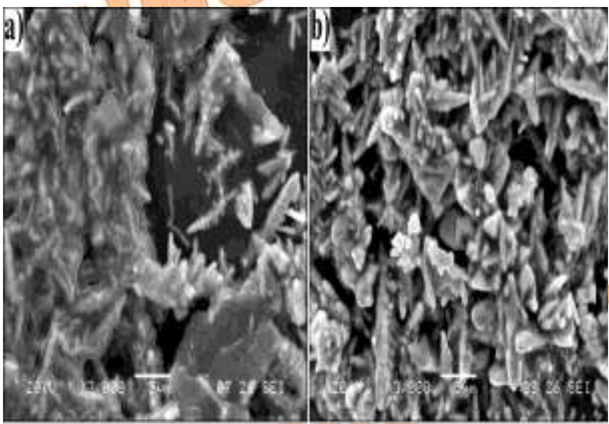

Fig. 10. SEM image of (a) ABS-Cu and (b) ABS-Al composites fabricated from optimized parameter combinations

4.7. Confirmation Test

The tensile strength results for ABS-Cu and ABS-Al composites are shown in Table 5, with kNN classification algorithm predicted values alongside the actual experimental results. Similarly, for both the composites, it can be seen that the kNN model has a fairly good accuracy, where the predicted values seem to be in close agreement with the experimental measurements. Nonetheless, the prediction error for the ABS-Cu composite is slightly smaller (2.94%) compared to the ABS-Al composite (3.99%). These results indicate that the kNN model can be a useful tool for predicting the tensile strength of these composites and thus a potential application of this method for material design and optimization.

Table 1. Tensile strength observation for ABS-Cu composites

S.No.	ABS - Acrylonitrile Butadiene Styrene (%)	Cu - Copper (%)	Surfactant Material (%)	Tensile Strength (N/mm2)
1	43.98	49.95	6.01	35.74
2	23.01	69.90	6.91	37.98
3	64.98	29.91	5.02	35.84
4	65.05	30	5	41.057
…	…	…	…	…
100	44.04	50.05	5.89	35.60

Table 2. Tensile strength observation for ABS-Al composites

S.No.	ABS - Acrylonitrile Butadiene Styrene (%)	Al - Aluminium (%)	Surfactant Material (%)	Tensile Strength (N/mm2)
1	43.98	49.90	6.18	10.76
2	22.85	69.94	7.09	10.60
3	65.02	30.03	5.06	19.52
4	64.85	30.10	4.92	27.95

…	…	…	…	…
100	43.95	49.97	5.89	10.85

Table 3. Classification report for ABS-Cu

Classifier	Precision	Re call	F1 score	Support
1	1.0	0.800	0.890	10
0	0. 830	1	0.910	10
Accuracy	NIL	NIL	0.900	20
Macro Average	0.920	0.900	0.900	20
Weight Average	0.920	0.900	0.900	20

Table 4. Classification report ABS-Al

Classifier	Precision	Re call	F1 score	Support
1	1.0	0.70	0.82	10
0	0.770	1	0.87	10
Accuracy	NIL	NIL	0.85	20
Macro in Average	0.88	0.85	0.85	20
Weight in Average	0.88	0.85	0.85	20

Table 5. Confirmatory test results of composites

Composite	Optimized parameters	Tensile strength (N/mm2) kNN	Experimental	Error (%)
ABS – Cu Composite	65.05% ABS+30% Cu+5% surfactant material	41.057	42.301	2.94
ABS – Al Composite	64.85% ABS+30.10% Al+4.92% surfactant material	27.95	29.115	3.99

5. Conclusions

This work examined the influence of various combinations of ABS, aluminium, and copper on the tensile strength of the developed ABS-Cu and ABS-Al composites. The following is the summary of the key findings of the study.

- The tensile strength of the composites recycled from ABS, copper, and surfactants was ~ 30%, while the same from ABS, aluminium, and surfactants was ~ 75%.
- The tensile strength predictions were made using the machine learning classification techniques, and the confusion matrix obtained had nearly 100% true positive, true negative, false positive, and false negative.
- The study's major findings demonstrate the efficacy of the K-Nearest Neighbors (KNN) classification algorithm in predicting the tensile strength of ABS composites with high accuracy. For ABS-Cu composites, prediction accuracy was 80% for k=1 and k=2, improving to 85% for k=3 and k=5, while ABS-Al composites showed similar trends with accuracies of 80% for k=1 and k=2, 85% for k=3, and reaching 90% for k=5. The KNN model achieved a recall of over 80% and an F1 score between 90-95%, indicating robust predictive performance. The optimal composition for ABS-Cu was identified as 65.05% ABS, 30% Cu, and 5% surfactant, yielding the highest tensile strength of 41.057 N/mm2, whereas the ABS-Al composite with 64.85% ABS, 30.10% Al, and 4.92% surfactant achieved a tensile strength of 27.95 N/mm2. Overall, the KNN model exhibited strong accuracy, with prediction errors of 2.94% for ABS-Cu and 3.99% for ABS-Al, closely aligning with experimental results and confirming the model's reliability in predicting composite material properties.
- The findings from this study demonstrate that surfactants significantly improve the dispersion of metal particles and the adhesion between the matrix and fillers, leading to composites with superior mechanical properties. These hybrid ABS composites could be used for connector terminals.
- The research concludes that composites made of ABS with higher proportions of copper or aluminium substantially increase their tensile strength and hence contribute to the development of tougher ABS-based composites for engineering use. ABS-Cu and ABS-Al composites offer enhanced tensile strength, making them ideal for applications requiring high

tensile force resistance. ABS-Cu composites also provide electrical conductivity, beneficial for electronic uses. Potential applications include the automotive, aerospace, and electronics industries. Specifically, ABS-Cu can be used in electrical connectors, conductive elements, and electromagnetic interference shielding, while ABS-Al is suitable for lightweight structural components and heat sinks. However, before industrial adoption, additional mechanical properties such as fatigue strength, impact resistance, hardness, wear resistance, and flexural strength need to be studied.

- Future investigations will compare the results with other models, such as Support Vector Machines, Decision Trees, and Random Forest, to provide a more comprehensive analysis. Additionally, it would be valuable to study the long-term performance of ABS-Cu and ABS-Al composites, including the effects of aging and environmental factors like moisture or UV exposure on tensile strength, by conducting accelerated aging tests and measuring tensile strength over time.

Nomenclature

kNN	k-Nearest Neighbouring
ABS	Acrylonitrile Butadiene Styrene
AM	Additive Manufacturing
IM	Injection Moulding
PMMA	polymethylmethacrylate

Acknowledgments

Not Applicable

Funding Statement

Not Applicable

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendixes

Not Applicable

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