AN ANN MODEL FOR MATRIX SELECTION FOR COIR FIBER REINFORCED POLYMER COMPOSITES

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ABSTRACT

Coir fiber is an abundant and renewable resource that can be used to develop environment friendly composites. The use of natural fibers as reinforcement in composites has gained significant attention due to their eco-friendliness and renewability. However, the selection of the appropriate matrix material is crucial to ensure the desired mechanical properties of the coir reinforced composites (CRCs). This article presents an innovative approach for selecting the optimal matrix material for CRCs using an ANN model that can help in the development of high-performance and sustainable composites for various applications. The data collated from the scientific articles was then used to train, validate, and test the ANN model. The model was trained with a dataset of mechanical properties of CRCs with different matrix materials and fiber volume fractions. The model accurately identified the suitable matrix material for a given fiber volume fraction and desired properties, thereby facilitating the selection of the appropriate matrix material for production of CRCs. The sensitivity analysis showed that the composite manufacturing process had the most significant effect for matrix selection.

1 INTRODUCTION

Researchers are profoundly investigating natural fiber-reinforced polymer composites (NFRPCs) due to the global interest being shifted towards sustainable products aligning with the sustainable development goals (SDGs). NFRPCs have attracted the interest of various industries due to their overwhelming tailorable properties compared to conventional materials, such as high strength to weight ratio, high stiffness, eco-friendliness, and corrosion resistance [1]. Coir (*cocus nucifera*), one of the natural fibers, is extracted from the coconut fruit husk, cultivated in the tropical countries that covers 36% of the earth's land. The coconut husk and shell often disposed of as waste can serve as high potential as reinforcement for polymer composites. Coir is harder and more rigid than other natural fibers due to its higher lignin content. Coir fiber reinforced polymer composites (CRCs) offer several advantages, such as, low cost, high specific strength, biodegradability, and sustainability that have helped them gain acceptance in the engineering applications in automotive industry, building and construction industry, packaging industry, and agriculture industry [2]. However, the mechanical properties of CRCs depend on several factors, such as, the type of polymer matrix, fiber orientation, and fiber volume fraction. The matrix in the composite is a continuous phase responsible to bind the fibers together for efficient load transfer. The selection of the matrix is an underrated problem depending on number of factors and it significantly impacts the performance of resulting composites. The selection of an appropriate matrix can enhance the properties of the composite, while an inappropriate matrix can lead to poor performance. Therefore, it is essential to select the right matrix material to optimize the mechanical properties of CRCs [3,4].

All the conflicting aspects affecting the fabrication of an optimal product present a perplexing task where computational techniques can be helpful for decision making. Artificial neural networks (ANNs) have been widely used in the field of composite material design due to their ability to model complex relationships between input and output variables. ANNs can learn from a set of input-output data and generalize to predict the output for new inputs. ANN models have been successfully used for predicting the mechanical properties of various composite materials, including natural fiber-reinforced polymer composites [5]. The current research endeavour analyses the experimental data of CRCs collated from the scientific repository and uses it to develop a robust ANN model that can accurately predict the optimal polymer matrix material for CRCs based on the various aspects. Further, a sensitivity analysis was conducted to evaluate the critical parameters for the matrix selection.

2 METHODOLOGY

Figure 1 illustrates the detailed methodology adopted for the current research analysis and model development. The methodology used in this study involved the data collection, data analysis, development of an ANN model, training and testing of the model, evaluation of the model's performance, validation of results, and sensitivity analysis. The methodology was designed to provide accurate and reliable results for the selection of matrices for coir fiber reinforced polymer composites.

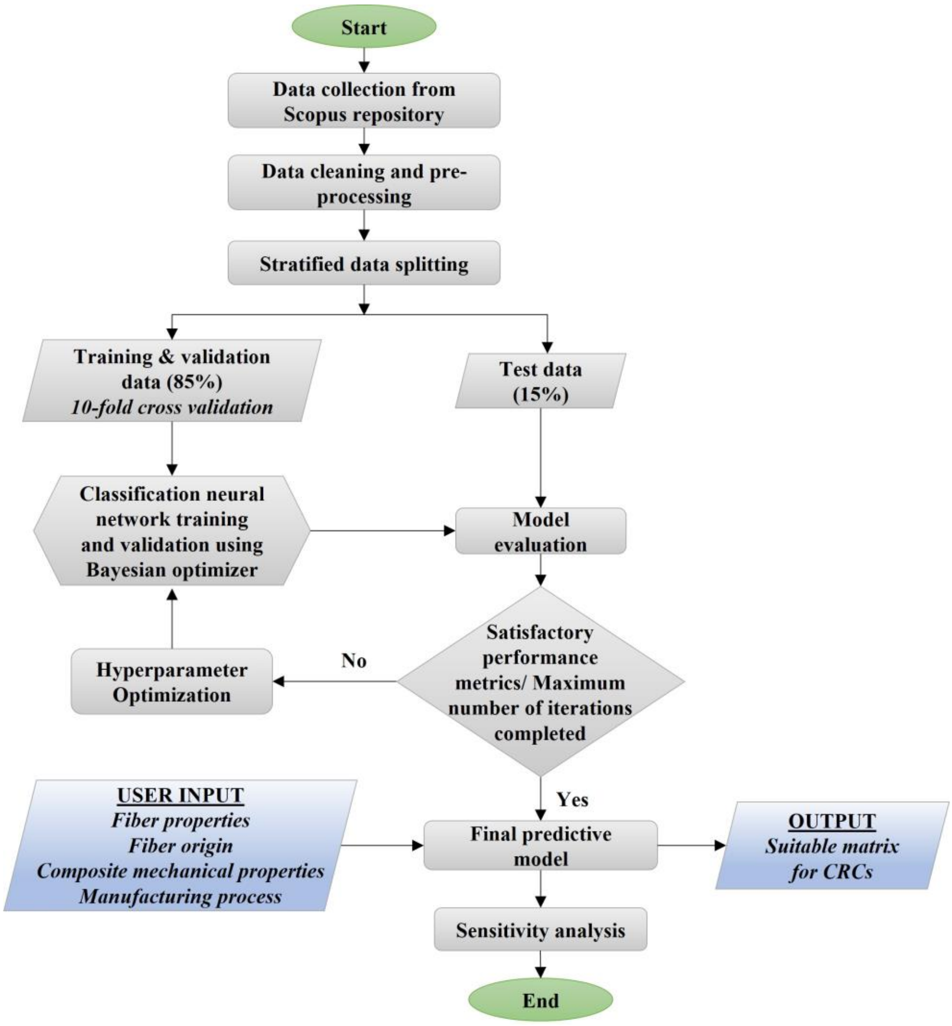

Figure 1 Methodology of the current analysis.

2.1 Data acquisition and preprocessing

The dataset comprising of 204 data points was collated from the SCOPUS repository's scientific literature, which documented the tensile and flexural behaviour of SCRCs in accordance with the ASTM D638 and ASTM D790 standard, respectively. This dataset encompasses the mechanical properties of SCRCs, including both untreated and treated fibers, in ten distinct polymer matrices. These polymer composites were manufactured using five different production processes. The characteristics of natural fiber are subject to regional variances. As such, the country of origin (geographical location) for the fiber utilized in the experimental analysis has been taken into consideration. Before constructing an Artificial Neural Network (ANN) model for matrix selection, exploratory data analysis was carried out to identify patterns and relationships within the data. This process helps researchers to understand the underlying structure of their data, gain insights into the research question, and make informed decisions about subsequent data analysis methods.

The data pre-processing step involved cleaning and transforming raw data to make it suitable for analysis. The data pre-processing techniques employed in this study included data cleaning and normalization in the range of 0 to 1. Normalization was performed to scale the data and reduce the impact of varying measurement scales on the model's performance. The data cleaning involved handling the missing values, and outliers in the dataset. The stratified data splitting was carried out ensuring the uniform class distribution of the data in both the training and the testing sets. It was performed to overcome the limitation of using imbalanced data. The training set contained 85% of the samples, and the testing set contained 15% of the samples.

2.2 Classification model framework

The classification model based on ANN was developed for optimal prediction of the matrix for short CRCs through MATLAB R2022a using the *fitcnet* function. The function generates the dummy features to transform the categorical features before model training The ANN model was trained using the training set, and the performance of the model was evaluated using the testing set. The k-fold cross-validation was used to validate the performance of the proposed ANN model. Cross-validation is a technique used in machine learning to evaluate the performance of a predictive model by partitioning the dataset into subsets, training the model on one subset, and evaluating its performance on the other set [6]. The 30 iterations of Bayesian optimization were performed to fine tune the hyperparameters for the model to minimize the classification error.

2.3 Performance evaluation

The model's performance metrics were evaluated from the confusion matrix and receiver operating characteristic (ROC) curve. A confusion matrix is a table that compares the predicted labels generated by a classification model with the actual or true labels. For multi-class classification problems, confusion matrix helps to compute metrics for each category, such as, accuracy, precision, recall, and F-score as summarized by Marina and Guy [7]. The ROC curve represents the trade-off between true positive rate (TPR) and false positive rate (FPR) of the classification model. The area under the ROC curve (AUC) was used as a measure of classification performance, with an AUC of 1 indicating perfect classification and an AUC of 0.5 indicating random guessing.

A sensitivity analysis was performed to examine the influence of individual features on the accuracy of predictions. The evaluation was based on the assessment of network error that results from the exclusion of individual input variables from the data. The sensitivity of the network to the absence of a particular variable is directly proportional to the increase in the network error upon its removal relative to the error obtained when all input variables are included. Consequently, a higher network error after the exclusion of an input variable indicates a greater sensitivity of the network to the absence of that variable. One can assess input variable significance by removing them from the network input, retraining, and determining a new network error ($Error_i$). Rejection of data is expected to result in increased network error. Thus, the basic measure of network sensitivity is the error quotient W_i, which compares the error obtained for a data set without one variable ($Error_i$) to the error obtained for a dataset with all variables (Error) as given in Eq. 1.

$$W_i = \frac{Error_i}{Error} \tag{1}$$

4 RESULTS AND DISCUSSION

Figure 2 provides valuable insights into the correlations between the numerical features that were investigated in this study, including fiber properties and mechanical properties of composites. Few plots reveal the presence of heteroscedasticity. Furthermore, each matrix exhibits a slightly distinct trend among them. Meanwhile, Figure 3 illustrates the interrelationships among the categories of features, namely the matrix, manufacturing process, and geographical location, that were explored in the literature. It highlights that polypropylene in thermoplastics and epoxy in thermosets are the most extensively studied matrices for reinforcing coir fiber. India, being one of the top producers of coir fiber, has made the highest contribution in the investigation of CRCs. Additionally, injection molding was found to be the most employed manufacturing process for fabrication of CRCs. The absence of significant correlations confirms the non-multicollinearity condition, which is suitable for the model.

For model strengthening and validation, a 10-fold cross validation technique was used. The network hyperparameters (number of hidden layers, number of neurons in each layer, weights, and bias) were optimized by Bayesian optimization approach. The hyperbolic tangent activation function resulted in minimum classification error of 0.0202 evaluated over 30 iterations as shown in figure 4(a). The accuracy achieved at each fold of cross validation during the model training is illustrated in figure 4(b). It also shows the average training and testing accuracy as 96% and 92%, respectively. The high training accuracy depicts the absence of underfitting, whereas the comparable test accuracy nullifies the presence of overfitting. Other than this, the model performance was evaluated by visualizing classification confusion matrix and receiver operating characteristics (ROC) curve for each category given in figure 4(c) and 4(d), respectively.

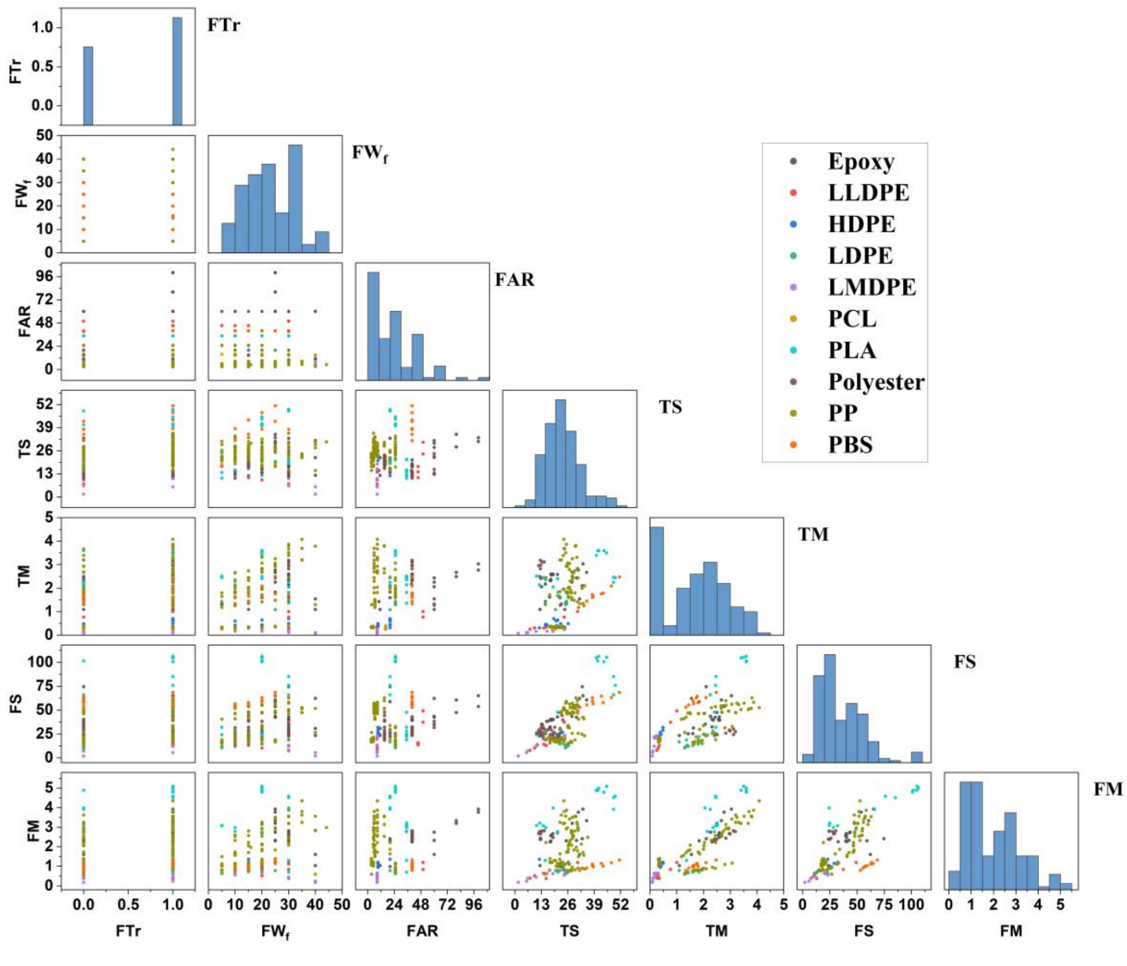

Figure 2 A scatterplot matrix for CRCs data set depicting pairwise dependencies between attributes.

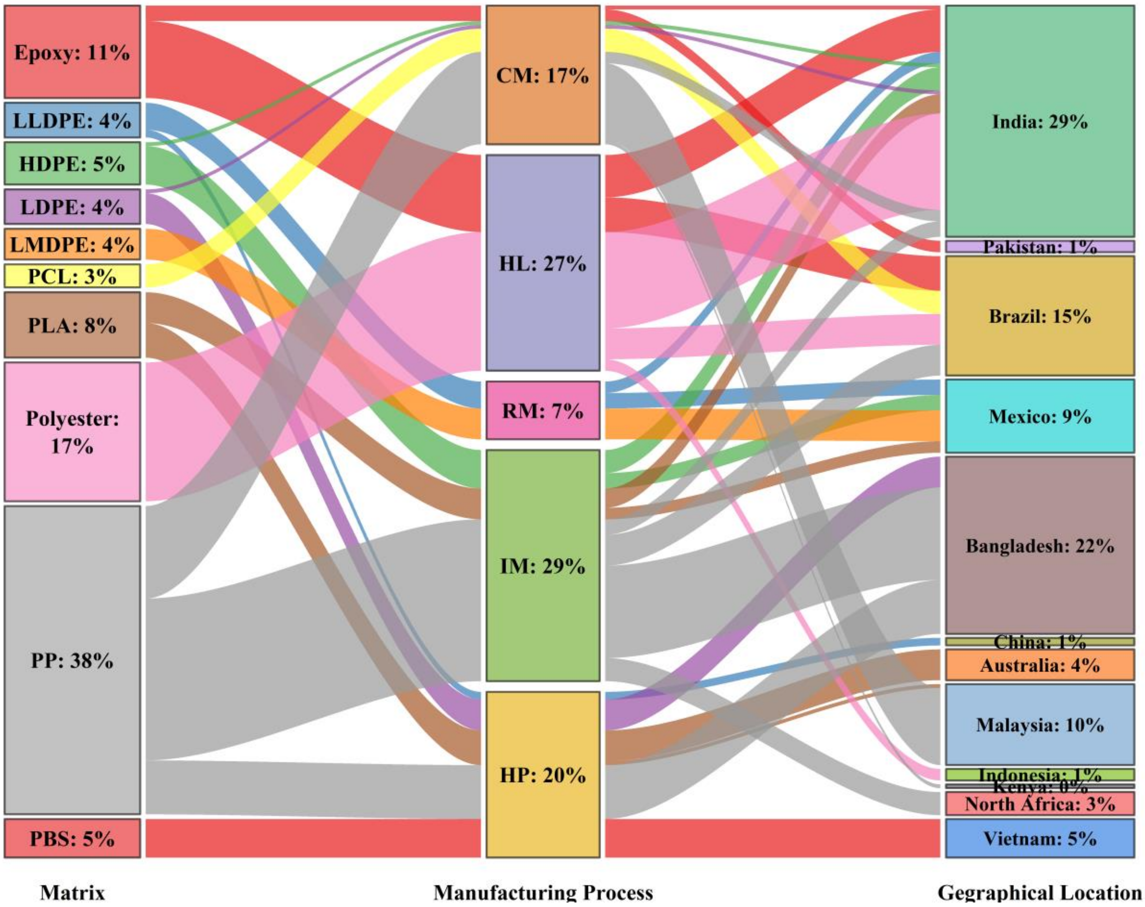

Figure 3 Interactions among the categories of features investigated as reported in the literature (LLDPE – Linear low density polyethylene, HDPE – High density polyethylene, LDPE – Low density polyethylene, LMDPE – Linear medium density polyethylene, PCL – Polycaprolactone, PLA – Polylactic acid, PP – Polypropylene, PBS – Polybutylene succinate, CM – Compression molding, HL – Hand layup, IM – Injection molding, HP – Hot pressing, RM – Rotational molding)

A confusion matrix is a table that compares the predicted labels generated by a classification model with the actual or true labels. Figure 4(c) demonstrates the confusion matrix with the precision and recall metrics for each category. The average values of accuracy, precision, and recall are 94.6%, 92.04%, and 92.25%, respectively. The high value of F score as 0.9214 indicates that the model has equally optimized precision and recall. The superior values of precision and recall assures an efficient model. The ROC curve measures the ability of an ANN model to correctly identify the appropriate matrix material for the coir fiber reinforced polymer composites, while minimizing the likelihood of selecting an inappropriate matrix material. The higher area under the ROC curve (AUC) indicates a high degree of accuracy in selecting appropriate matrix for coir fiber reinforcement. Figure 4(d) reported an average AUC value of 0.997 that denotes the model effectiveness. The use of the ROC curve and AUC metric in this analysis highlights the importance of evaluating the performance of machine learning models in terms of their ability to balance between true positives and false positives.

The sensitivity coefficient of each feature was calculated using the equation(1). Although all the features exhibited sensitivity coefficients higher than 1, indicating that they were all essential, the composite manufacturing process displayed the highest sensitivity coefficient (Figure 4(e)). The data analysis revealed that samples manufactured through injection molding exhibited superior mechanical properties compared to those produced through compression molding. Furthermore, the geographical location had a considerable impact on the output, suggesting that the utilization of the same fiber with different properties (arising from distinct locations) may necessitate varying matrices to achieve the desired mechanical properties. Additionally, the weight fraction of the fiber was found to have a significant impact on matrix selection. The insights gained from the sensitivity analysis can be utilized to optimize the manufacturing process and select appropriate matrix materials based on the properties of the fiber source. The model provides an accurate and efficient approach to select matrix materials based on various input variables and desired mechanical properties. This can significantly reduce the time and cost associated with the trial-and-error method typically employed for matrix selection.

In conclusion, the results showed that the proposed ANN model was capable of accurately predicting the most suitable matrix for the fabrication of CRCs, with an overall accuracy of 94.6%. The model's high prediction accuracy indicates that it can be used as a reliable tool for material selection in the composites industry. The results of the analysis can be used as a basis for further research in the field of composite materials and can contribute to the development of more reliable and efficient material selection methods in the industry.

5 POTENTIAL APPLICATIONS OF CRCs

The utilization of natural fiber composites presents significant potential for use in a variety of industries including low-cost housing, consumer goods, and other applications where conventional lightweight reinforced plastics may be limited. These composites are increasingly being utilized in the automotive, aerospace, and sporting goods industries, as well as for constructing boat hulls, storage tanks, tails, wings, and propellers. Research has explored the potential of coir fiber composites in a range of applications, such as, particle boards, sound absorption panels, cement sand mortar, and as packaging materials [2]. Yan and Su [8] have suggested the application of coir fiber reinforced concrete in the construction of panels, decks, slabs, and beams. There is also growing interest in the use of coir composites for thermal insulation, as well as for seat cushions in automobiles and construction. Coir-polyester composites exhibit potential for the temporary storage of non-water and non-saltwater liquids.

4 CONCLUSIONS

The development of sustainable materials for use in various applications has become increasingly important due to the growing concern for the environment. Natural fiber composites, such as CRCs, offer a promising alternative to conventional materials used in several industries. However, the selection of the appropriate matrix for these composites is crucial for optimizing their mechanical properties and enhancing their durability. The current analysis highlights the importance of matrix selection using ANN for the development of CRCs. The developed ANN model can be applied to real-world applications, aiding in the development of sustainable materials for various industries, including automotive, aerospace, and construction. Moreover, coir fiber has been majorly investigated with polypropylene among thermoplastic resins and polyester among thermosetting polymers. The next research step could be the investigation of green composites fabricated using biopolymers with significant focus towards sustainability.

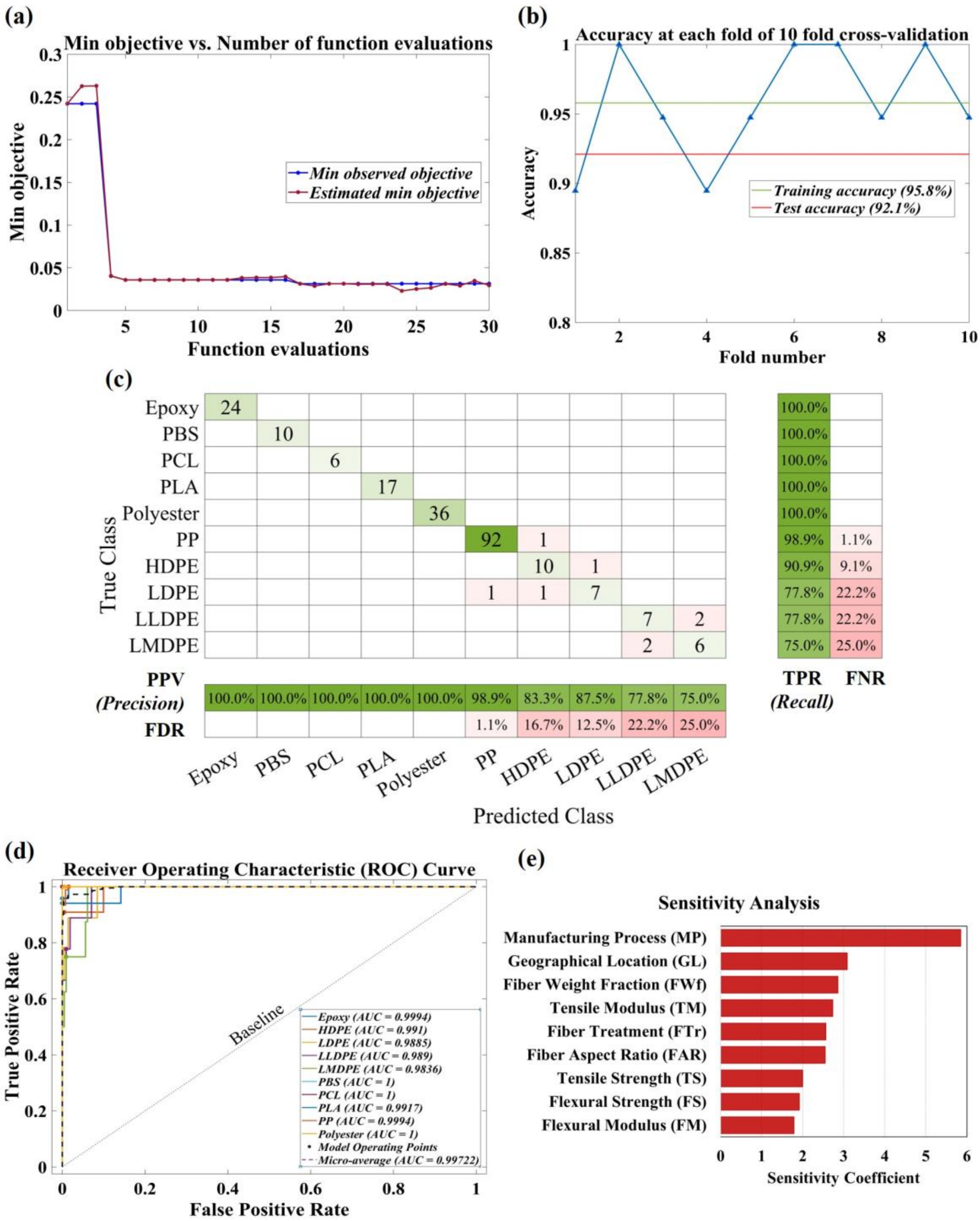

Figure 4 Model performance evaluation plots (a) minimum objective i.e., loss at each iteration, (b) training and testing accuracy, (c) the classification confusion matrix (d) ROC curve for each classification category (e) sensitivity coefficient of features.

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