Characterisation of Filament Current in an Electron Beam Accelerator using Decision Tree and Random Forest

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ABSTRACT

The filament is an essential component in an electron beam accelerator. The current flowing through the filament produces an electron beam through the thermionic emission process. The filament current's stability significantly affects the electron beam's stability, making the resulting dose homogeneous. A machine learning approach with a regression algorithm is used to analyse the characteristics of the filament current. The regression algorithms used are the decision tree regressor and the random forest regressor. The study chose this algorithm to understand and predict the relationship between parameters and desired results in the electron accelerator commissioning process. The analysis shows that the regression model applied to the filament current data performs well. With the decision tree regressor, an MAE of 0.531, an MSE of 0.316, and an R^2 of 0.961 are obtained, while random forest with an MAE of 0.379, an MSE of 0.280, and an R^2 of 0.965 are achieved. The experimental results suggest that the random forest regressor outperforms the decision tree regressor in the characterisation of filament current in electron beam accelerators.

INTRODUCTION

The utilisation of electron beams using accelerators has been widely carried out in industry and research [1]. Electron beam radiation technologies [2] that utilise accelerators include crosslinking industrial products [3], surface curing of materials [4], sterilisation of medical products [5], and food irradiation [6]. Electron beam accelerators accelerate electron particles through strong electric fields [7–9]. The beginning of electron formation comes from one of the accelerator components called the electron source [10]. Electron sources are used not only in electron beam accelerators but also in MRI-Linac Therapy [11], electron beam probes [12], electron microscopes [13], welding [14], and microwave devices [15]. Electron sources consist of several main components, including filaments, cathode electrodes, anode electrodes, and vacuum chambers, as shown in Fig. 1 [16].

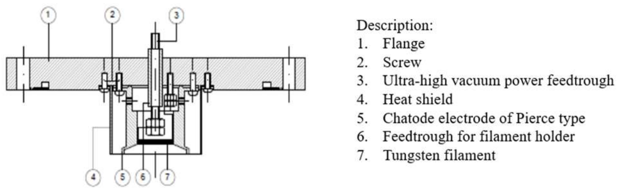

Fig 1. Schematic structure of the electron source [16].

The electron source works by heating a tungsten filament to generate electrons, which are then directed by Pierce-type electrodes and protected by a heat shield on a DN-160 CF flange that matches the accelerator tubes from the National Electric Corporation. Power is provided through an ultra-high vacuum power feedthrough to isolate the anode and cathode. When electric current flows through the filament, the filament becomes very hot and heats the cathode indirectly. The cathode receives heat and causes the electrons on its surface to have enough energy to escape and exit the cathode surface, a phenomenon known as thermionic emission [17]. The released electrons are directed by the focusing electrode and then drawn toward the extraction anode, resulting in a focused electron beam. The resulting electron beam can then be used for irradiation [18].

The filament current in an electron beam accelerator is closely related to the dose received by the irradiated sample [19]. Radiation dose measures the radiation energy absorbed by the material per unit mass. The greater the filament current, the greater the dose received by the sample. Filament current is the determining factor of the dose rate. Filament current characterisation is an important step to ensure optimal performance of the electron beam accelerator. An in-depth analysis of filament current stability and fluctuations is needed to ensure optimal dose rate. Machine learning methods can be an appropriate choice in supporting this analysis [20] because machine learning can learn data patterns, relationships between parameters, and optimisation based on data collected from electron accelerator operations [21–23].

METHODOLOGY

In characterising the filament current at the electron source of an electron accelerator, a regression machine learning algorithm [24] is used to predict the current based on existing operational parameter data. The machine learning regression methods used are the decision tree and random forest regressor. The software used for analysis is Python 3 (Jupyter Notebook). The research steps can be seen in Fig. 2.

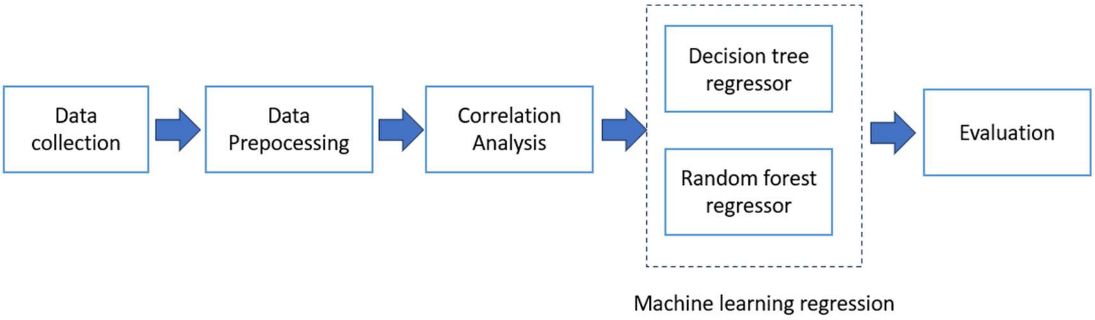

Fig 2. Characterisation of filament current using a machine learning regression algorithm.

The first step is to collect electron accelerator operation data, including time data, high voltage source current, voltage at high voltage source, filament current, coulomb current, vacuum pressure, and electron beam current. The data is compiled in the form of a .csv file. This study uses the filament current as the output (target), while the other parameters are inputs. The next step is to plot the data in the form of a graph to determine the pattern of the data. Next, data cleaning and data normalisation are performed. Data cleaning uses the data.isnull() feature. Data cleaning is done to remove outliers and incomplete data. Data normalisation is performed on numeric features to ensure all variables are on the same scale so that the algorithm works optimally. The feature used for normalisation is MinMaxScaler.

After the data preprocessing, the next step is identifying important features that correlate with filament current in electron beam accelerator operation data. The feature analysis used is a correlation matrix and feature importance. The correlation matrix feature shows the relationship between parameters in the dataset [25], while the importance feature shows how much influence each variable has on the prediction model [26].

The fourth step is to apply machine learning algorithms. The selected method is non-linear regression [27]. In this study, a decision tree regressor and a random forest regressor were chosen. Both methods can capture non-linear interactions, analyse interactions between features, and be robust if there are data variations [28]. The data is divided into training and test data with a ratio of 80:20, with a random seed of 42. The last step is evaluation by calculating Mean Absolute Error (MAE), Mean Squared Error (MSE), and R^2 score to measure the accuracy of the training results [29]. Then, the performance of training results for the decision tree and random forest regressor is compared.

RESULT AND DISCUSSION

The data taken consists of five main parameters in the operation of the electron accelerator. The main concern is the electron source filament current, as shown in Table 1. From the data, it can be seen that when the filament current increases, the electron beam current also increases. This is because the number of electrons produced and extracted increases along with the rise in filament current. With the increase in electrons, the vacuum level will decrease.

Table 1. Example of electron beam accelerator parameter data display.

Time (minute)	Highvoltage Current (mA)	Beam Current (μA)	Filament Current (A)	Vacuum Pressure (mbar)
0	0.5	0.04	0.54	0.0000086
1	0.4	0.04	0.62	0.0000087
2	0.4	0.05	1.14	0.0000087
3	0.4	0.1	1.8	0.0000085
4	0.4	0.13	2.53	0.0000085
5	0.4	0.05	3.12	0.0000085
6	0.4	0.13	3.71	0.0000085
7	0.5	0.14	4.16	0.0000087
8	0.4	0.57	5.14	0.0000087
9	0.4	1.32	5.73	0.0000087
10	0.4	3.86	6.53	0.0000087
11	0.5	17.36	7.3	0.0000087
12	0.5	36.54	7.79	0.0000087
13	0.9	130.8	8.43	0.0000087
14	1.51	313.65	8.98	0.000009
15	2.2	516	9.42	0.0000093
16	4	1043.3	10.04	0.0000095
17	6.1	1694.4	10.48	0.00001
18	9.7	2859.9	10.94	0.00001

After obtaining the data, it is processed, and then the data will be plotted in the form of a graph to determine the pattern of the data. Fig. 3 shows the relationship between each pair of parameters as a scatter plot. This scatter plot explores the relationship between each variable in a dataset. Each small box represents the relationship between two different variables. There is a linear relationship between filament current and beam current, filament current and high voltage source current, and high voltage current and beam current. This means it has a positive correlation; one variable increases, and its pair of variables also tends to increase. The histogram on the main diagonal shows the distribution of each variable.

After that, data preprocessing is carried out, namely, cleaning the data and normalising the data scale, relatively easy to analyse. The next step is identifying important features correlating with filament current in electron beam accelerator operation data. Feature analysis uses a correlation matrix and feature importance. The parameters in the electron beam accelerator include filament current, time, high voltage source current, beam current, and vacuum pressure. Fig. 4 shows the correlation between parameters, with filament current as the output (target) and other parameters as the input.

The correlation matrix has a value range of -1 to 1; if it is close to 1, the relationship between the two variables is very strong. From the heatmap visualisation, close to 1 means it is positively correlated, and the two variables move in the same direction. If it is close to 0, then the variables have no linear relationship. All parameters are related to time and, on average, positively correlated. Then, the highest correlation relationship with filament current is high voltage current, and the beam current is 0.68. This shows a close relationship between filament current, high voltage source, and beam current. The other variable, vacuum pressure, is 0.53, which is also quite influential on filament current.

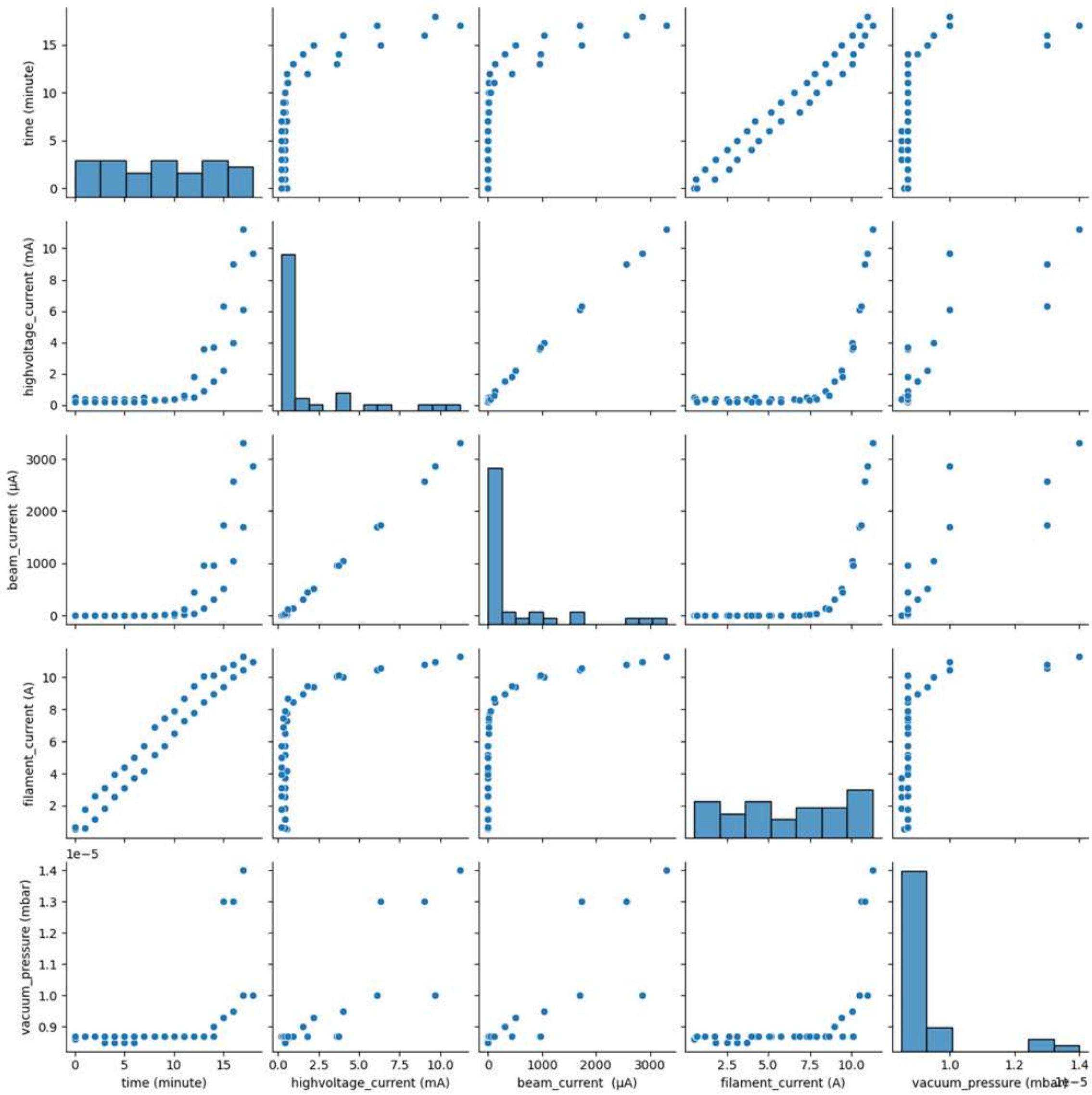

Fig 3. Pairplot of the relationship pattern between parameters.

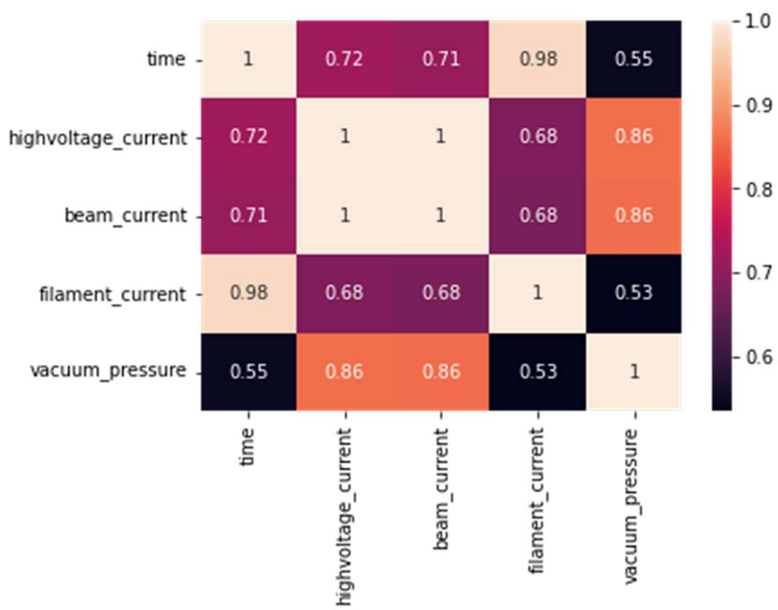

Fig 4. Heatmap correlation matrix.

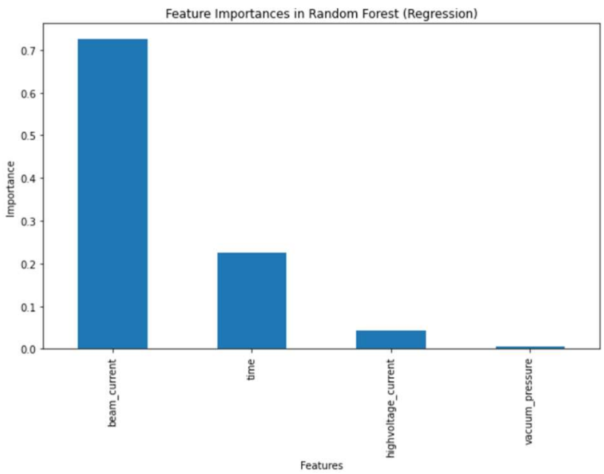

Fig 5. Feature importance with random forest.

Feature importance is instrumental in machine learning because it can help us understand which features contribute the most to the prediction results [30]. From Fig. 5, it can be seen that the highest values are beam current and time, which affect the prediction of filament current. High voltage and vacuum pressure also have an effect, but are not significant. The character of the electron beam accelerator operation data is polynomial, so that a non-linear regression analysis can be performed.

In machine learning regression for non-linear data, several methods are used in this study, namely the decision tree regressor and random forest regressor [31]. The data is divided into training and test data with a ratio of 80:20. Training is done for each method with random seeds totalling 42. A decision tree regressor is a type of machine learning that can be used for regression. Unlike the classification decision tree that predicts discrete labels, the regressor decision tree is used to predict continuous values. This model divides some data into parts based on feature values to minimise the error in predicting the target value [31]. The plot of the decision tree process can be seen in Fig. 6.

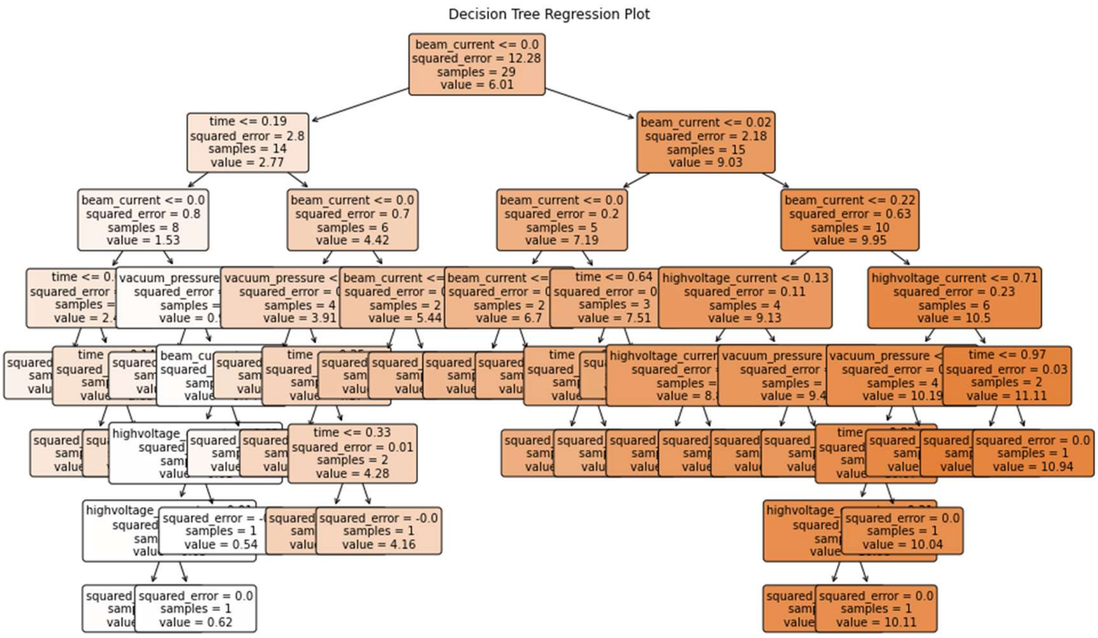

Fig 6. Decision tree regression plot.

Random forest regressor is a decision tree-based ensemble method for continuous output prediction. In random forest, multiple decision trees are randomly constructed, and the final result is the average prediction of all trees, which helps reduce overfitting and improve model accuracy [32,33]. The plot of the random forest process can be seen in Fig. 7.

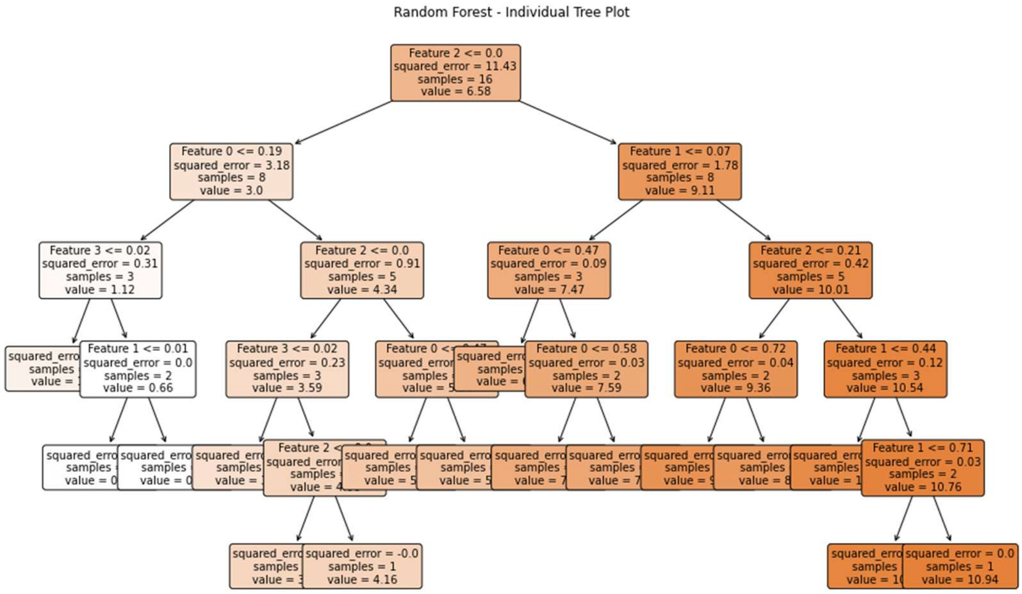

Fig 7. Random Forest regression plot.

Mean Absolute Error (MAE), Mean Squared Error (MSE), and R^2 score are calculated to measure the accuracy of the training results. MAE is used to average the absolute difference between the value predicted by the model and the actual value. It measures how far the average prediction of the model is from the actual value. MSE is the average of the squares of the difference between the predicted and actual values. It gives more weight to more significant errors because the errors are squared. R^2 is a measure of the proportion of variance in the dependent variable that the independent variables in the model can explain. R^2 values range between 0 and 1, where 1 indicates that the model explains all the variation in the data, and 0 indicates that the model explains no variation.

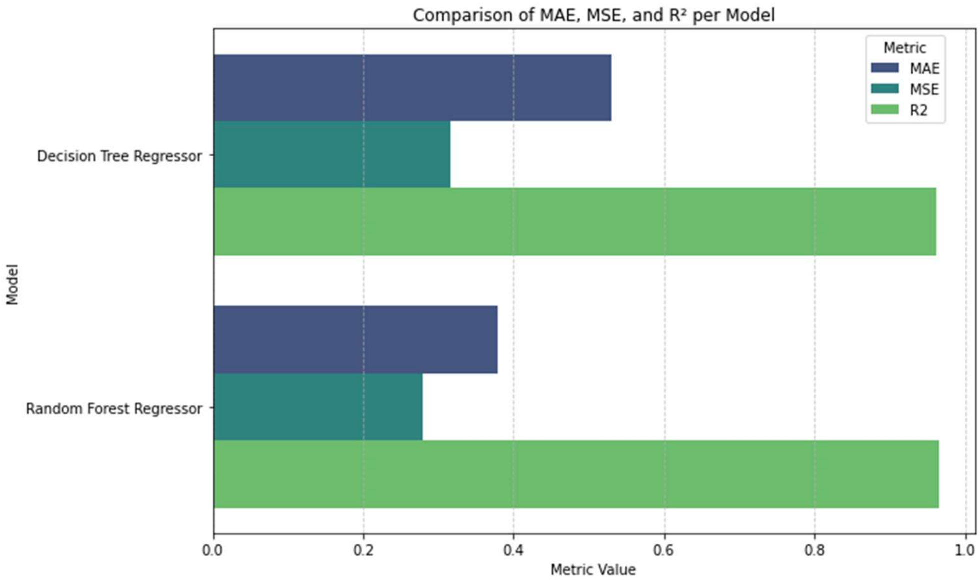

Fig 8. Training evaluation results with decision tree and random forest.

The training results in Fig. 8 obtained for the decision tree regressor model obtained an MAE of 0.531, an MSE of 0.316, and an R^2 of 0.961, while the random forest regressor obtained an MAE of 0.379, an MSE of 0.280, and an R^2 of 0.965. Both show good performance, as indicated by R^2 values close to 1, but the random forest is slightly superior. The MAE and MSE are lower than the decision tree based on the overall results. Random forest produces more accurate predictions and fewer errors than decision trees. Random forest is better because it is an ensemble learning method that combines many decision trees. The randomisation technique in feature selection and data samples in random forest can also reduce model variance and improve generalisation [34].

CONCLUSION

Based on the characterisation of filament current using machine learning regression, it can be seen that filament current is very crucial in determining the electron beam current. When the filament current is increased, the electron beam current increases. This is because the number of electrons produced and extracted increases along with the rise in filament current. The machine learning method obtains accurate results with the decision tree regressor and random forest regressor methods. The training results for the decision tree regressor model obtained an MAE of 0.531, an MSE of 0.316, and an R^2 of 0.961, while the random forest regressor obtained an MAE of 0.379, an MSE of 0.280, and an R^2 of 0.965. Random forest is better because this method is an ensemble learning method that combines many decision trees. Randomisation techniques in feature selection and data samples in random forests can also reduce model variance and improve generalisation.

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AUTHOR CONTRIBUTION

I.D. Rachmawati served as the main contributor in this study. She was responsible for data acquisition from the electron beam accelerator, training of machine learning models, data analysis for filament current characterisation, and the primary drafting of the manuscript. N. Effendy and Taufik contributed to the conceptual framework of the research, evaluation of the implemented models, and provided critical review and revision of the manuscript. Saefurrochman assisted in data collection and contributed to the writing and editing of the paper.

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