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Soft Computing Techniques for Prediction of Forest Fire Occurrence in Brunei Darussalam

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Abstract. Forest fires are destroying wildlife habitat and pollutes air with emissions dangerous to human health. Increased carbon dioxide in the atmosphere by the wildfire contributes to the greenhouse effects and climate change. The ashes remove a lot of nutrients and eroded soils, causes landslides and flooding. Brunei Darussalam rich in biodiversity and tropical forest resources is increasingly recording more forest fires every year. These fires destroy the precious forest resources of the country, degrade the environmental quality particularly deteriorate air quality and cause significant economic loss in terms of property, infrastructure and possess threat to human health as well as ecosystem. Therefore, the objective of the study is to analyze the forest fire contributors such as topographic, human factor, climate, ignition factor, and vegetation and use a soft computing technique (machine learning) to classify the possible of occurrence.
Keywords: *Forest fires; contributing factors; soft computing techniques; artificial neural network; support vector machine*

INTRODUCTION

Forest fires also called as a wildfire are described as burning of trees and plants in a natural environment such as forest, which takes the natural fuels based on environmental conditions. It has an indirect and direct impact on the environment. Wildfire plays an important role in changing the ecosystem by serving as an agent of change and regeneration. It destroys wildlife habitat and pollutes air with emissions dangerous to human health. Increased carbon dioxide in the atmosphere by the wildfire contributes to the greenhouse effects and climate change. The ashes remove a lot of nutrients and eroded soils, causes landslides and flooding. The smoke from the wildfire can be extremely dangerous to lungs especially for kids, elders and those with breathing problem or asthma or chronic heart disease. The major health concern arises from particulate matter, particularly PM2.5. It triggers problem such as heart attack, asthma attack and death. Climate change in wildfire plays an important role to fuel the flames of these wildfires influenced by dry weather conditions with high temperature. The soils become drier during summer temperature. As a result, it increases the possibility of drought and an extended forest fire season. The intensity of forest fire is further aggravated by hot and dry conditions and chances of catching fire is much higher due to anthropogenic activities such as fire from cigarette, sabotage or natural causes like lightning.

South-east Asia particularly East Kalimantan in Borneo region has been vulnerable to forest fires due to slush and burn to clear land for agricultural activities. The forest fire in East Kalimantan has led to trans-boundary haze problems and its impact has been observed in Brunei Darussalam regularly. On 15-18th March 2019, Brunei-Muara

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experienced forest fire destroying around 151 hectares of forest. The forest fire was reported from Rimba, Tungku Link, Lambak Kanan and Berakas. There were 84 cases of forest fire over four days and rescue personal were sent to the affected areas [1].

The fire occurrence shows that various factors that can be influenced as their contributors, for example; topographic, human factor, climate, ignition factor, and vegetation [2]. The wind is also considered as a fire contributing factor for predicting forest fire occurrence. The direction of the winds depends on how the fire is being spread. It provides a new supply of oxygen and facilitates burning. Topography is also one of the fundamentals in the fire behaviour triangle [3]. A certain elevation and degree of a slope can affect the spreading of the forest fire. The temperature has an effect on forest fire because of the heat requirement for ignition and continuing the combustion process. Other than temperature, Humidity is one of the fires contributing factor for a forest fire. Fuels in a location with a higher percentage of humidity and rainfall tend to be moist and damp. The higher percentage of the humidity, the lower the chance they can ignite a fire.

Using the high computing techniques and artificial techniques, spread of forest fires and their effect on the ecosystem can be predicted and analyzed. Prediction of forest fires using spatial prediction model for forest fire susceptibility has been carried out using convolutional neural network [4]. Different prediction technique using GIS and a new hybrid artificial intelligence model was used named as MAR-DFP, which was Multivariate Adaption Regression Spline with Differential Flower Pollination [5]. Wireless Sensor Network has been used in predicting forest fire to compare machine learning such as neural network, regression, support vector machine and decision tree [6]. In some of the wildfire, logistic regression to predict forest fire ignition has been done [7]. Classification model can be used in forest fire occurrence using Artificial Neuro-Fuzzy Interference System in machine learning based on hotspot data. Cascade correlation network was also used to predict and detect forest fire occurrence and compared with another prediction model [8]. In other studies, Multi-layer perception neural network also one of the techniques used in predicting forest fire [9].

The objective of the study is to analyse the forest fire contributors such as topographic, human factor, climate, ignition factor, and vegetation and use a soft computing techniques (such as ANN, SVM, KNN) to classify the possible of occurrence.

METHODOLOGY

Data Collection and Processing

The daily observation of Brunei's weather data between 2009 and 2019. In addition, the data was extracted from Brunei International Airport Using Satellite and factors are shown in Fig. 1. These factors are considered as the contributing factors for the fire occurrence [10]. Before training a model, data pre-processing is a crucial part of the data mining process. Mostly, data gathering methods are light controlled, resulting in outlier, incomplete data, impossible data combination. Analysing data that have not sorted carefully will cause confusing results. The quality and depiction of a sample is a must before running a model. The success of data interpretation in neural network determined by the quality, availability and reliability of the data. If there is an unsuitable sample that is noisy and unrealistic, then the model will give unrealistic outcomes too. Data preparation and filtering step can take some time of processing time once it is done, the sample becomes more optimized and better results are achieved. In the data online, there is conversation needed to be sorted out such as temperature, dew point, wind speed and etc. in order to get reliable data. The temperature and dew point should be in degree Celsius and Wind Speed should be converted into mph. However, the precipitation has to be excluded in this research due to its lacking in term of reliability. These contributing factors will be used as the input data for the neural network. However, the contributing fire factors are lacking data in term of finding output data. Thus, rules are created to find the target data for the output result.

1st rule: The Maximum Temperature (Temp Max) is ≥32.2 ℃

2nd rule: The Maximum Dew Point (Dew Point Max) is ≥to 26.1 ℃

3rd rule: The Minimum Humidity (Humidity Min) is ≤ to 52%

When the sample meets the requirement of the rule, the sample value becomes 1, which indicate fire occurrence based on the rules. After sorting, data normalization is the next step for data processing to reduce and even eliminate data redundancy. This step helps to adjust the parameter of the numeric column in the dataset to use a common scale, without changing the range of value or losing data.

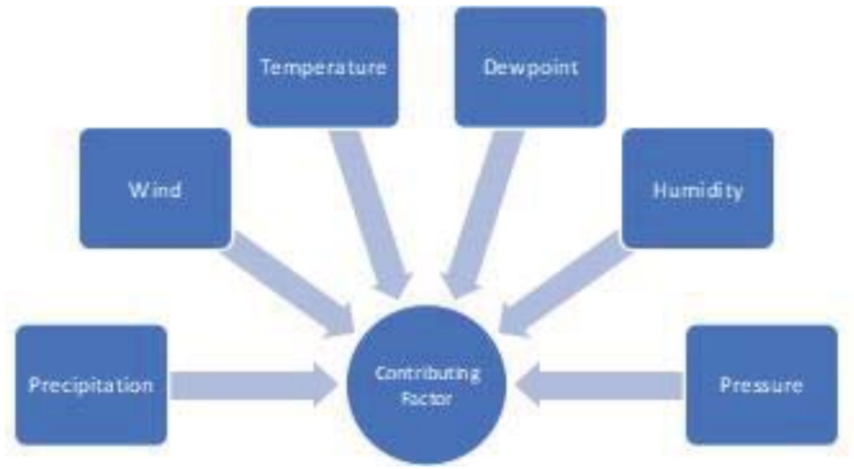

***FIGURE 1**. Contributing factors for analysing the forest fires occurrence*

SOFT COMPUTING TECHNIQUES

In this study, various machine learning techniques (such as ANN, SVM, KNN) are applied to predict the to classify the possible of occurrence.

Artificial Neural Network and Its Architecture

In this research, the Artificial Neural network (ANN) with feed-forward neural network or multilayer perceptron is implemented. This design consists of a lot of simple neuron-like processing units, sorted in layers. Different kind of network functions is used to compare the accuracy of neural and performance. To train the following result, we used the most common technique known as backpropagation algorithm (BP), which consist of an optimization step at reducing the global error seen in the output layer. Backpropagation algorithm trains a feed-forward neural network. To train the network, the algorithm needs to know the connection between certain sets of input-output pairs. The backpropagation works as follows, the first step it propagates the input values into the hidden layers, and then propagates the sensitivities back to ensure the error minimized, at the end of the process it updates the weight. The first backpropagation algorithm is used known as Levenberg Marquart learning algorithm. It is an iterative method that shows the minimum of a multivariate that is shown as the sum of squares of nonlinear-least squares situation. This method has become a general technique for solving nonlinear problems, widely used in a range spectrum of fields. It can be seen as a combination of steepest descent and Gauss-Newton. This method will become the Gauss-Newton Method when the solution is close to the expected solution.

Artificial Neural Network's Training Procedure

This is based on the nature of input and output data. The data consist of 5 sets of parameter or attribute related to contributing fire factors. The output signal consists of data with the value within a range of 1 or 0 to indicate whether fire occurs or not. The number or size of the hidden layer was chosen, ranging between 10 to 50. For the training of the different neural network, the following steps were designed.

1. The first step was to pick the variable of the network and the learning function (Levenberg Marquart, Bayesian Regularization) before training the network with training.
2. Every training cycle, the validation in mean square error was examined, if it was less than the optimal value achieved so far, the result is updated, and the current network was stored.
3. Repeat the previous step until the MSE of the sample shows no more improvement in the continuous set of a training cycle
4. When the optimum results were achieved, they were compared with other types of learning function and the number of hidden neurons.

SUPPORT VECTOR MACHINE

It is a very popular supervised machine learning algorithm which is used for regression problem or classification problem. In Support Vector Machine, it involves a method using kernel trick that transforms the sample and then based on the transformation, and it shows the best boundary between the possible output. It builds a very complicated data transformation, then figures how to separate the data based on the output and labels being defined. A kernel is known as a variety of mathematical function that is used by support vector machine. Varieties of support vector machine used a different kind of kernel function. For ex: linear, quadratic, medium gaussian and coarse gaussian.

KNN

It is one of the classifications which keep all available cases and classifies new problem according to the similarity measure. This technique applied in statistical estimation and pattern recognition already in the past decades as a non-parametric. In this research, 6 different KNN classifiers like Fine KNN, Medium KNN, Coarse KNN, Cosine KNN, Cubic KNN, Weighted KNN are used to classify the sample.

Statistical validation

The confusion matrix shows the amount of correct and incorrect prediction produced by the model compared with the actual classification in the test data. This matrix is a performance measurement used by classifying problem where output is more or equal to two. The Fig. 2 shows how a confusion matrix. By using 2x2 confusing matrix that shows four possible outcomes:

1. TP (True Positive) is an outcome where the model correctly predicts the positive class
2. TN (True Negative) is an outcome where the model correctly predicts the negative class
3. FP (False Negative) is an outcome where the model incorrectly predicts the positive class.
4. FN (False Negative) is an outcome where the model incorrectly predicts the negative class

These outcomes are the performance of the classifier. Based on these concepts, it can further define the following performance measurement. Accuracy is one metric for evaluating classification models. It is defined as the fraction of prediction of models that correctly predicted. The accuracy has the following meaning:

$$Accuracy = \frac{Number\,of\,correction\,prediction}{Total number\,of\,Prediction}$$

For binary classification, accuracy can be found in terms of negative and negatives as given equation below:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

True Positive Rate (Sensitivity or Recall) of a classifier represent the positive correctly classified samples to the total number of positive samples, and it is estimated.

$$TPR\ (Sensitivity\ or\ recall) = \frac{TP}{TP + FP}$$

True Negative Rate (Specificity or Inverse Recall) is defined as the ratio of the correctly classified negative samples to the total amount of negative sample

$$TNR\ (Specificity\ or\ Inverse\ Recall) = \frac{TN}{TN + FN}$$

Positive Prediction Value (PPV or Precision) shows the proportion of sample were correctly classified to the total number of positive samples

$$PPV = Precision = \frac{TP}{TP + FP}$$

Negative Predicted Value (NPV or Inversely Precision) shows the proportion of the negative sample that were correctly classified to the total number of negative predicted sample.

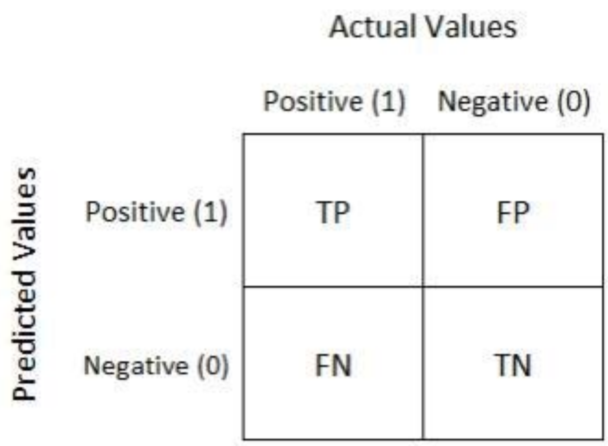

FIGURE 2. *Schematic Diagram of Confusion Matrix*

RESULT AND DISCUSSION

The main focus of this study is to predict forest fire based on contributing fire factor and machine learnings. The computation is carried out on a workstation with an AMD Ryzen 7 2700x Eight-Core Processor 3.70 GHz, 16 GB of ram while Windows 10 is used as the operating system. The data has 5 parameters and 2308 sample in the workspace for forest fire contributing factor. The performance of the model determines the best result of the model. From Figure 11, shows that Scaled Conjugate perform lesser than the other two algorithms and LM. Scale Conjugate Scaled Gradient has the least performance, which is 1.03e-2 MSE when tested with 50 number of hidden neurons. However, the best model for Scaled Conjugate is using 30 hidden neurons with 5.95e-3 MSE and accuracy of 94.7%.

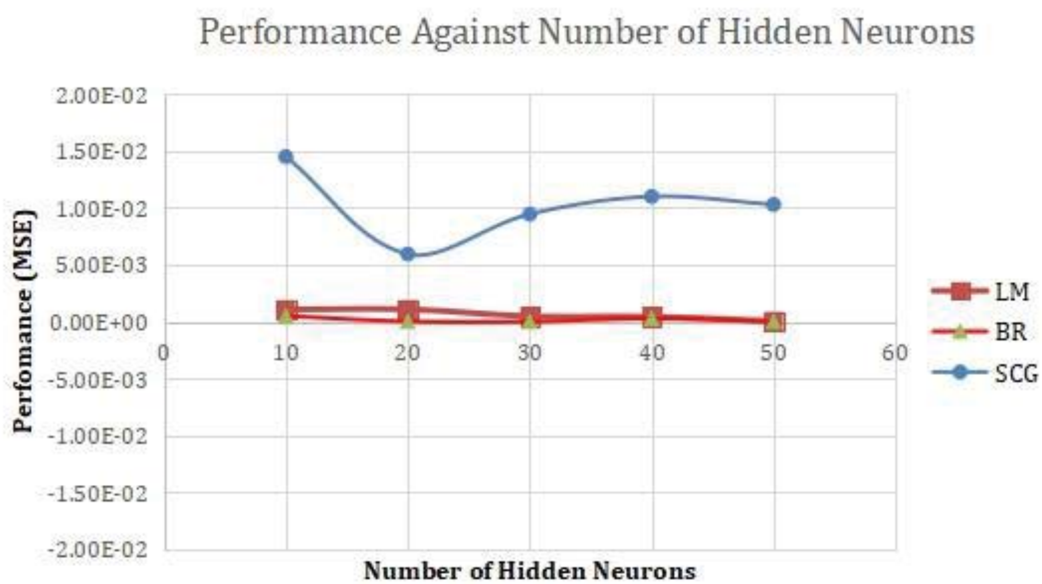

FIGURE 3. *Comparison of performance using three different algorithms*

The training data for Scaled conjugate show poor result compared to Bayesian Regularization and Levenberg Marquardt algorithm. The validation and testing results of SCG show the inconsistent result of R values. Using the theory of an increasing number of hidden layers, the greater number can give the network more flexibility when the network has more parameter. However, increasing the layer size can cause the problem to be uncharacterized. This can be shown when model tested with 20, 30 and 40 number of hidden neurons using. The performance of Levenberg Marquart algorithm is better as the number of hidden layers is increasing, as illustrated in Fig. 3. The best model of Levenberg is using 50 number of Neuron with 99.7% overall accuracy and 5.50e-3 MSE. Around 10 hidden neurons are the least performance using Levenberg Marquart Algorithm with 1.08-e3 MSE and accuracy of 99.7%. For Bayesian Regularization, the model predicted that 50 neuron produces the best result for the neural network which has an accuracy of 99.9 % and 1.08e-5 MSE. The overall best model of the three algorithms is compared and proved that Bayesian Regularization Algorithm has the lowest MSE for the model performance.

Classification Using Regression and Machine Learning

This section is to compare the accuracy and other performance using different kind of classification methods with specified fold number of cross-validation. Table 1 shows the available method of classification with its performance measure. A method in the discussion, the neural network consists of 5 fire contributing factors and 1 output (fire occurrence). The sample used in classification is 2308, which splits around 2000 sample are used to in Classification for Training Set and 308 for the Test set. In the procedure step, the classification uses 5 k-fold for training every method available in the classifier. The results show SVM has the highest result for training compare to KNN, Linear Discriminant and etc.

TABLE 1. *Result of Test Set for Classification*

Methods	TP	FN	FP	TN	ACC	TPR	TNR	FPR	FNR	AUC
Linear SVM	284	1	15	8	94.81%	99.65%	34.78%	65.22%	0.35%	0.672
Quadratic SVM	281	4	0	23	98.70%	98.60%	100.00%	0.00%	1.40%	0.992
Cubic SVM	280	5	0	23	98.38%	98.25%	100.00%	0.00%	1.75%	0.991
Fine Gaussian SVM	285	0	17	6	94.48%	100.00%	26.09%	73.91%	0.00%	0.630
Medium Gaussian SVM	285	0	9	14	97.08%	100.00%	60.87%	39.13%	0.00%	0.804
Coarse Gaussian SVM	285	0	15	8	95.13%	100.00%	34.78%	65.22%	0.00%	0.673
Linear Discriminant	282	3	14	9	94.48%	98.95%	39.13%	60.87%	1.05%	0.690
Quadratic Discriminant	284	1	5	18	98.05%	99.65%	78.26%	21.74%	0.35%	0.889
Logistic Regression	281	4	13	10	94.48%	98.60%	43.48%	56.52%	1.40%	0.710
FINE KNN	285	0	13	10	95.78%	100.00%	43.48%	56.52%	0.00%	0.717
Medium KNN	285	0	13	10	95.78%	100.00%	43.48%	56.52%	0.00%	0.717
Coarse KNN	285	0	19	4	93.83%	100.00%	17.39%	82.61%	0.00%	0.586
Cosine KNN	284	1	13	10	95.45%	99.65%	43.48%	56.52%	0.35%	0.715
CUBIC KNN	285	0	14	9	95.45%	100.00%	39.13%	60.87%	0.00%	0.695
Weighted KNN	285	0	12	11	96.10%	100.00%	47.83%	52.17%	0.00%	0.739

The result showed that Quadratic SVM has the highest accuracy with the lowest and result in Classification. Higher the AUC, better the model is at predicting. The Area under Curve (ROC) is 0.992 and accuracy of 98.70% because of the higher value of Sensitivity and Specificity. The classification results show that Support vector machine using Fine Gaussian SVM has the least accuracy and area under the curve. To prove this, the true negative value of the model was lower than other SVM methods. It shows predicted more wrongly for forest fire occurrence. For KNN classification, the best model created using this model is Weight KNN with an accuracy of 96.10%. it has the least error rate than other KNN model and AUC =0.739. On the other hand, Coarse KNN was seen to be the least performance as it has the lowest accuracy and small area under the curve (AUC = 0.586). For Discriminant, Quadratic Discriminant is shown to have better performance with an accuracy of 98.05% than using Linear Discriminant which is 94.48% accuracy. The Linear Discriminant has lower result is because it has a higher value of TNP than Quadratic Discriminant. Classification using logistic regression has an accuracy of 94.48% with AUC of 0.710. It has only better performance than using Coarse KNN. From the test data, 281 samples correct predicted no forest fire happened and 23 samples correctly predicted forest fires occurrence. However, the model mis-predicts 4 sample no forest fire in the test data.

Review of Relevant Study Conducted Globally for Predicting Forest Fires Using Machine Learning

In Heilong Jiang Province, China uses logistics regression as their machine learning to predict forest fire occurrence. The model obtained result of ROC is 0.905 and 85.7% accuracy. The confusion matrix proved that logistics regression correctly predicted 83.7% of all regions. The ignition points were correctly predicted around 83,3% while 83.3% were correctly predicted for non-forest fire [11]. Another study uses Support Vector Machine to predict forest fire using factors influencing regional scale wildfire in Iran. The process validation of the model using the ROC- AUC method shows 0.751 for prediction of forest fire and 0.814 success rate. This report also compared with another model conducted in Vietnam and Spain. The model that was implemented in Vietnam obtained value AUC of 0.88 for the prediction rate and an AUC value of 0.71 was obtained in Spain. A different method of prediction using Case-based reasoning with RBF with 78% accuracy with 5000 cases. In other cases, radial basis function with cased based reasoning achieved an accuracy of with 66% with 5000 number of cases. This method was conducted in five different places in the United States and it is effective in estimating the probability of a cell's ignition. The accuracy of this algorithm is between 58.45% and 82.08% which is feasible.

From different studies, MARS -DFP was conducted in Vietnam has AUC (accuracy) of 0.95 and 86.75% CAR, which is better than different machine learning model. Backpropagation Artificial Neural Network is the second-best method which obtains an AUC value of 0.90 and a CAR value of 83.97%. CAR is defined as the classification accuracy rate. Another result using MARS has obtain 0.89 value of AUC and 82.05%. ANFIS model was also a prediction of forest fire has achieved 0.87 and 80.98%. Followed by Radial Basis Function Artificial Neural Network has 0.85 AUC and 79.22% CAR. The last model was created using Random Tree which achieves 0.86 value of AUC and 84.55% CAR [5]. Another case study using machine learning in Vietnam, the forest fire model reveal that Multi-layer perceptron neural network has the highest positive predictive ability, which correctly predicted forest fire occurrence with 84.0%. it has a value of 0.904 for AUC and 83.8 % accuracy. The random forest also created for forest fire modelling. The result shows 0.855 AUC and 77.6% accuracy. In that research, SVM was model was constructed and found out it has an accuracy of 77.4% and 0.844 AUC value [9].

In China, a machine learning using Spike Neural Network was implemented. The result of the model shows that it can achieve an accuracy of 86.36% to 90.61% for the classification results. It shows that SNN has the ability to detect forest fire with good performance [7]. A different model of machine learning built-in china using Convolutional Neural Network for Yunnan Province of China. The studies stated that it has an accuracy of 87.92 and 0.85 AUC value. In China, they also used a prediction model such as RF, SVM, MLP and KLP. For Random Forest, it has recorded a value of 84.36 % accuracy and 0.82 AUC. Support Vector Machine showed that it has predicted with an accuracy of 80.04% and 0.79 AUC. From the study, Multi-layer perceptron neural network has achieved 78.47% accuracy and 0.78 AUC. Lastly, kernel logistic regression indicated 81.23% accuracy with 0.78 value of AUC (Zhang, Wang and Liu, 2019). A model created using ANFIS has shown better result than Neural Network. It has an accuracy of 95.02%. compare to ANN and FIS with an accuracy value of 90.22% and 89.25%.

CONCLUSIONS

Brunei Darussalam rich in biodiversity and tropical forest resources is increasingly recording more forest fires every year. These fires destroy the precious forest resources of the country, degrade the environmental quality particularly deteriorate air quality and cause significant economic loss in terms of property, infrastructure and possess threat to human health as well as ecosystem. In this study, there is an attempt to analyse the forest fire contributors such as topographic, human factor, climate, ignition factor, and vegetation and use a soft computing technique technique (such as ANN, SVM, KNN) are applied to predict the to classify the possible of occurrence. The results are verified statistically. The result showed that Quadratic SVM has the highest accuracy with the lowest and result in Classification. Higher the AUC, better the model is at predicting. The Area under Curve (ROC) is 0.992 and accuracy of 98.70% because of the higher value of Sensitivity and Specificity. The classification results show that Support vector machine using Fine Gaussian SVM has the least accuracy and area under the curve.

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