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Extreme Learning Machine Approach for Prediction of Forest Fires using Topographical and Metrological Data of Vietnam

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***Abstract*—A problem is a well-posed problem if it satisfy, solution existence, solution uniqueness and non- perturbation conditions. Ill-posed problems or inverse problems are the special case of well-posed problem, because inverse of major function does not exist. Forest fire prediction is an inverse problem. Forest are the largest natural resources. Forest fire is a calamity, it is a threat to the entire regime of flora and fauna. Forest fire mitigation is essential because it can devastate biodiversity, wild life and can cause economic loss. In this research work extreme learning machine is used, because it has capability prediction problem solves with better generalization and fast learning speed. ELM is a new approach to be used for forest fire prediction. Presented work predict the forest fire occurrence with the help of topographical and metrological data, with parameters slope, Aspect, Elevation, NDVI, Distance to road, Distance to residential area, Land use, Temperature, Wind speed, Rainfall and forest fire occurrence. The motivation behind this work is to predict the forest fire to provide better way of management for this tragedy. In this research work a relationship is being established between forest fire causing factors and forest fire occurrence using historical data. The used database is already existing data of 540 historical locations of Vietnam. Experiments are conducted on different data partitions of availed data with different activation functions. On the basis of accuracy of model, sigmoid function found to be best and suggested to be used further for forest fire prediction.**

***Keywords*—NDVI,ELM,forest fire,topographical,metrological.**

I. Introduction

Forest are the largest and most important natural resource. Forest provide timber fuel, food and bio products to ecosystem. The benefit of Ecological functions like water and air purification, maintenance of habitat for wild life, nutrient cycling and carbon storage can be obtained by forest. Forest control global warming and fight with natural disaster as well. They are responsible for rain, to avoid noise and air pollution and provide food and shelter to living organism. Forest provide economic and environmental strength to countries worldwide.

Forest fire is a threat not only to forest wealth but also to the biodiversity by disturbing the entire regime to flora and fauna. Forest fires can occur due to man-made and natural causes. Weather factors play an important role in occurrence of forest fire.There are many factors that are responsible for the forest fire. These factors contribute as a symptoms that can be used to predict the occurrence of forest fire in future. Topographical and metrological data can be used to find the trend for prediction using machine learning algorithm.

Prediction of forest fire can help in proactive decision making and planning, it can also help in taking planned precautionary and preventive measures. ELM has better performance in terms of speed and generalization than traditional learning algorithm. ELM is used because it reduces the time required to train the network. The motivation of this proposed work is to reduce the economic and environmental detriment. ELM is used to predict forest fire as ELM is still not used for forest fire prediction.

II. Extreme Learning Machine

A new learning procedure for single hidden layer feed forward neural networks known as Extreme Learning Machine (ELM) which overcomes the problems caused by gradient descent based algorithms such as Back propagation applied in ANNs. ELM can significantly reduce the amount of time needed to train a Neural Network.

ELM is designed to work exclusively for the "generalized" single-hidden layer feed forward networks and it also does not requires the tuning of the hidden layer. These types of SLFNs include SVM, polynomial network, RBF networks and both single-hidden-layer/ multi-hidden-layer feed forward neural networks. Unlike conventional SLFNs here in ELM hidden nodes can be generated randomly. The parameters of the hidden nodes are independent of the target function and training dataset. The parameters of ELM are computed analytically rather than tuning, for efficient real application the output weights can be computed with or without iterations.

As per ELM theory, the neuron parameters or hidden node are not dependent on training data, they are also not related to each other, such standard SLFN's have separation and universal approximation capability. Such hidden nodes that are independent to the training data and their respective mappings are termed as ELM random neurons, random nodes or random features. Unlike traditional learning methods which consider the training data before generating the neuron parameters / hidden node, ELM could generate the neuron parameters / hidden node randomly before looking to the training data.

Extreme Learning Machine is a novel algorithm to train the SLFNS. It is the effective, efficient and fast for the training purpose.

For L defined training sample (x_j, y_j) here

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$$x_j = [x_{j1}, x_{j2}, x_{j3} \dots x_{jq}]^T \in A^q$$

$$y_j = [y_{j1}, y_{j2}, y_{j3} \dots y_{jp}]^T \in A^p$$

SLFN's prepared with $\tilde{L}$ number of hidden layer neurons and r(x) activation function.

$$\sum_{j=1}^{\tilde{L}} \beta j.r\,(w_j.x_k+b_j) = P_k \text{where } k = 1 \dots L$$

$w_j = [w_{j1}, w_{j2}, w_{j3} \dots w_{jq}]^T$, weight assigned between input layer and hidden layer.

$Bj = [\beta j_1, \beta j_2, \beta j_3 \dots \beta j_p]^T$, weight assigned between hidden layer and output layer.

b_j= bias

The SLFN's having $\tilde{L}$ hidden layer neuron and r (x) training function approximate L samples with almost zero error.

$$\sum_{k=1}^{\tilde{L}} ||P_k - y_k||$$

$$\sum_{j=1}^{\tilde{L}} \beta j.r\,(w_j.x_k+b_j) = y_k \text{where } k = 1 \dots L$$

$w_j.x_k$is the inner product the above mentioned equation can be reduced to $G\beta = Y$.

G is output matrix in the model,

$$G\,(w_1 \dots w_{\tilde{L}}, b_1 \dots b_{\tilde{L}}, x_1 \dots x_L) = \begin{pmatrix} r(w_1.x_1 + b_1) \dots & r(w_{\tilde{L}}.x_1 + b_{\tilde{L}}) \\ \vdots & \vdots \\ r(w_1.x_L + b_1) \dots & r(w_{\tilde{L}}.x_L + b_{\tilde{L}}) \end{pmatrix}_{\tilde{L} \times L}$$

$$\beta = \begin{pmatrix} \beta_1^T \\ \vdots \\ \beta_L^T \end{pmatrix}_{\tilde{L} \times p} \qquad y = \begin{pmatrix} y_1^T \\ \vdots \\ y_L^T \end{pmatrix}_{L \times p}$$

To reduce the error function Extreme Learning Machine declare the weight w and bias b arbitrarily and analytically calculate the output weights β, such that

$$\beta = G^*.y$$

G* is Moore Penrose generalized inverse calculation of β reduce the time consumption during the training phase.

III. Proposed ELM Algorithm For Forest Fires Prediction

Our suggested forest fire forecast architecture used to predict forest fire with the assistance of 10 input features i.e. slope, Aspect, Elevation, NDVI, Distance to road, Distance to residential area, Land use, Temperature, Wind speed, Rainfall and forest fire occurrence and 2 target class 0(no fire) and 1(fire). The performance of the ELM classifier depends upon the activation function and number of hidden layer neurons. ELM classifier with 40 hidden layer neurons is used to developed classifier with different activation functions.

Algrithm1: Proposed ELM Algorithm

1. Acquire the Forest Fire data.
2. Use the [0, 1] normalized data.
3. Divide dataset into training and testing sets.
4. Decide neurons for hidden layer and develop the ELM model
5. Select activation function for training the network and for predicting the result after that.
6. With training dataset file (parameter and targets) and training function train the model as G (w, b, x).
7. Calculate the output weight as β =G*.y.
8. With testing dataset file test the results from the trained model and predict the class labels.
9. Compare the predicted class labels from known targets of testing set.
10. Visualize the results with roc curve and confusion matrix.

IV. Results And Discussion

The proposed framework use the metrological and topographical data to predict forest fire. The used data belongs to Lam Dong, Vietnam (***Tien Bui et al 2018***)and is extracted from mendeley. Database has ten attributes that have affect in forest fire occurrence and are used in the model to discriminate between fire and no fire instances in Vietnam.

The experiments are performed on different partitions of database for five different activation function. The evaluation of the result are demonstrated with the help ROC curve and confusion matrix.

A. Using Hardlim Function

1) 648 instances for training set and 432 instances for testing set.

Fig. 1. Confusion matrix 648-432 dataset

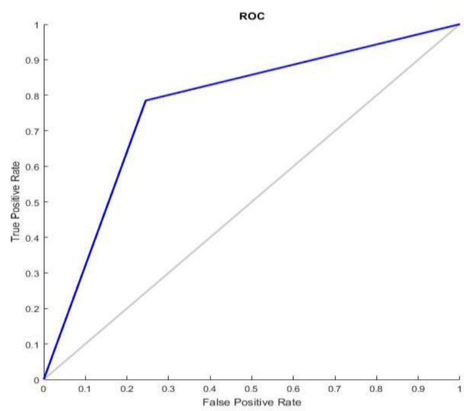

Fig. 2. ROC Curve 648-432 dataset

It can be concluded from fig. 1 prediction of forest fires that were classified correctly 77.08%.

2) 540 instances for training set and 540 instances for testing set.

Fig. 3. Confusion matrix 540-540 dataset

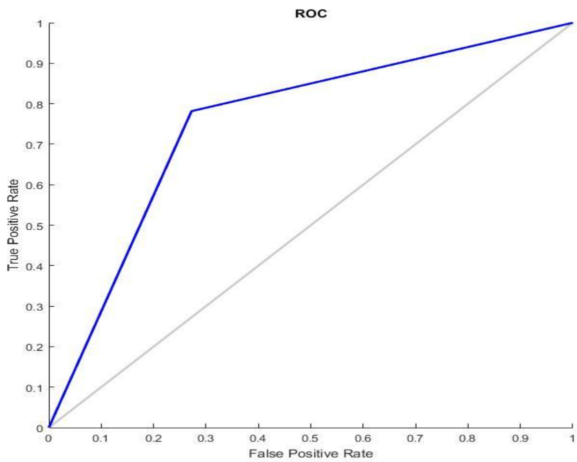

Fig. 4. ROC Curve 540-540 dataset

It can be concluded from fig. 3 prediction of forest fires that were classified correctly 75.37%.

3) 756 instances for training set and 324 instances for testing set.

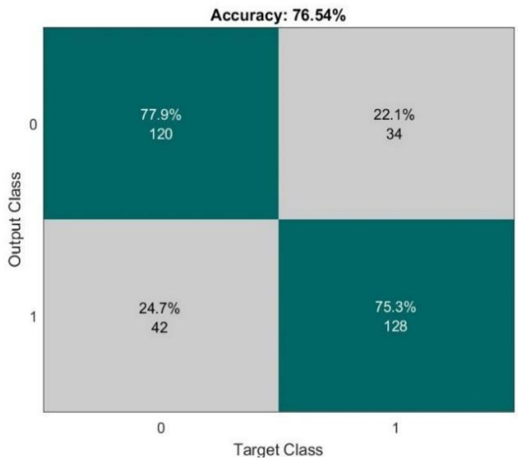

Fig. 5. Confusion matrix 756-324 dataset

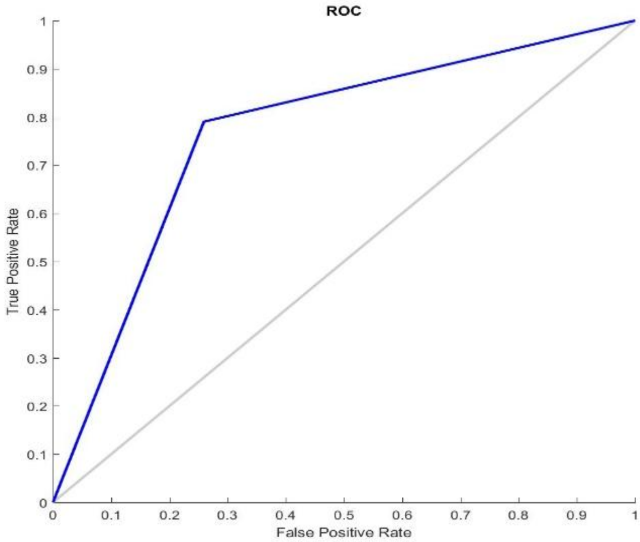

Fig. 6. ROC Curve 756-324 dataset

It can be concluded from fig. 5 prediction of forest fires that were classified correctly 76.54%.

TABLE I. SPECIFICITY AND SENSITIVITY USING HARDLIM ACTIVATION FUNCTION FOR DIFFERENT TRAINING AND TESTING PARTITION

Sample Datasets	*Specificity*	*Sensitivity*
648-432	78.51%	75.49%
540-540	78.15%	72.76%
756-324	79.01%	75.00%

B. Using Radial Basis Function

1) 648 instances for training set and 432 instances for testing set.

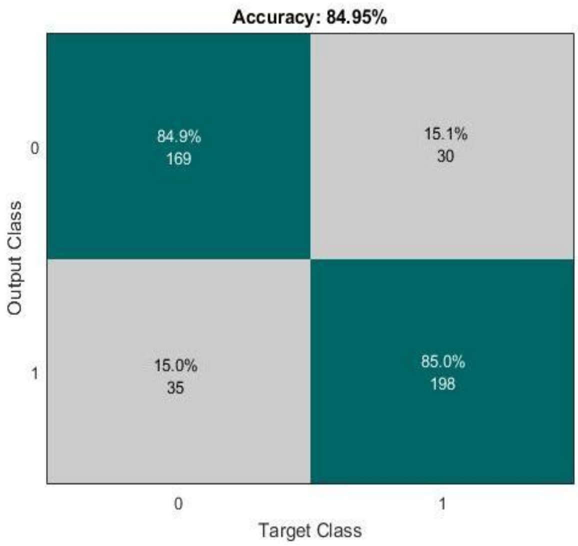

Fig. 7. Confusion matrix 648-432 dataset

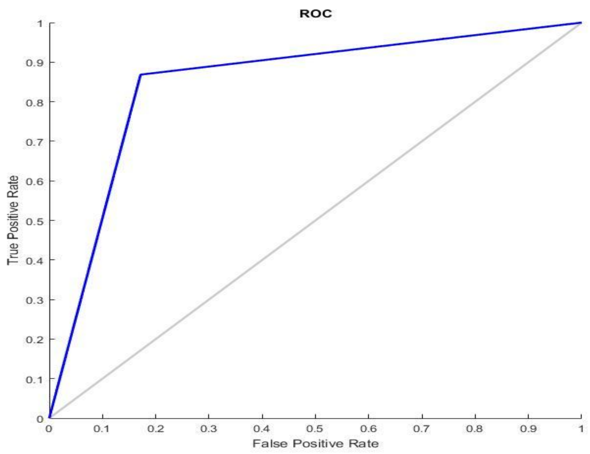

Fig. 8. ROC Curve 648-432 Dataset

It can be concluded from fig. 7 prediction of forest fires that were classified correctly 84.95%.

2) 540 instances for training set and 540 instances for testing set.

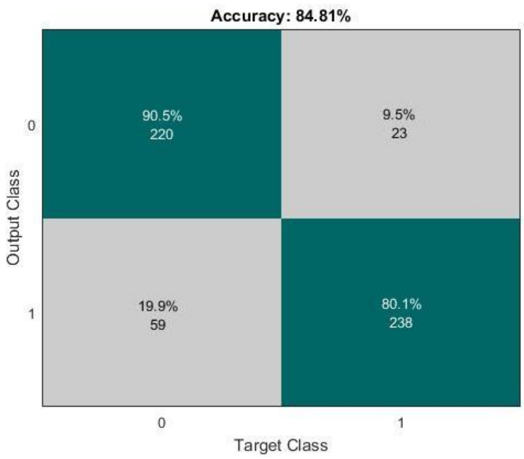

Fig. 9. Confusion matrix 540-540 dataset

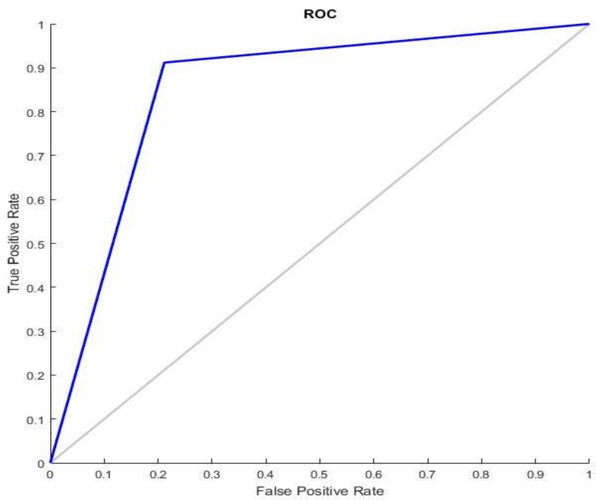

Fig. 10. ROC Curve 540-540 Dataset

It can be concluded from fig. 9 prediction of forest fires that were classified correctly 84.81%.

3) 756 instances for training set and 324 instances for testing set.

Fig. 11. Confusion matrix 756-324 dataset

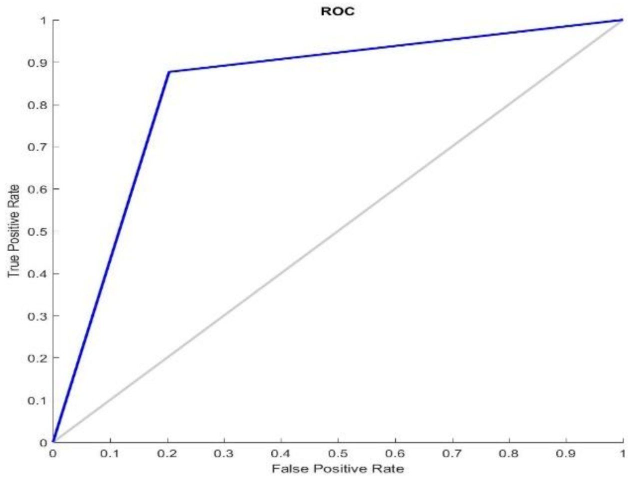

Fig. 12. ROC Curve 756-324 Dataset

It can be concluded from fig. 11 prediction of forest fires that were classified correctly 83.64%.

TABLE II. SPECIFICITY AND SENSITIVITY USING RADIAL BASIS ACTIVATION FUNCTION FOR DIFFERENT TRAINING AND TESTING PARTITION

Sample Datasets	*Specificity*	*Sensitivity*
648-432	86.84%	82.84%
540-540	91.19%	78.85%
756-324	87.65%	79.63%

C. Using Sigmoid Function

1) 648 instances for training set and 432 instances for testing set.

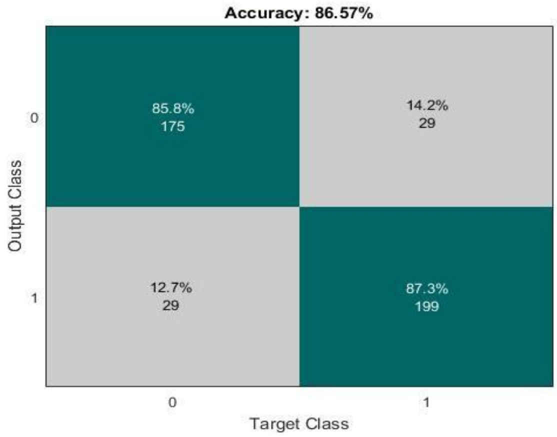

Fig. 13. Confusion matrix 648-432 dataset

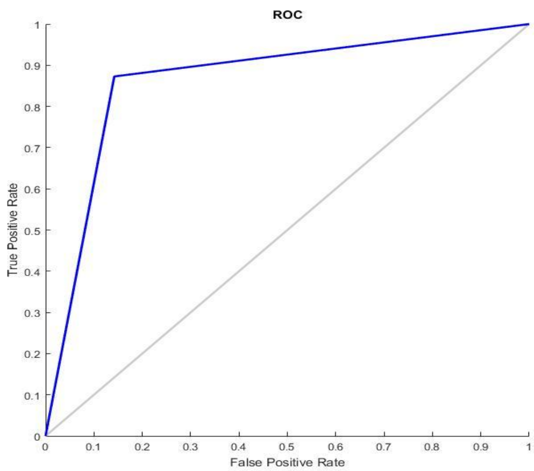

Fig. 14. ROC Curve 648-432 dataset

It can be concluded from fig. 13 prediction of forest fires that were classified correctly 86.57%.

2) 540 instances for training set and 540 instances for testing set.

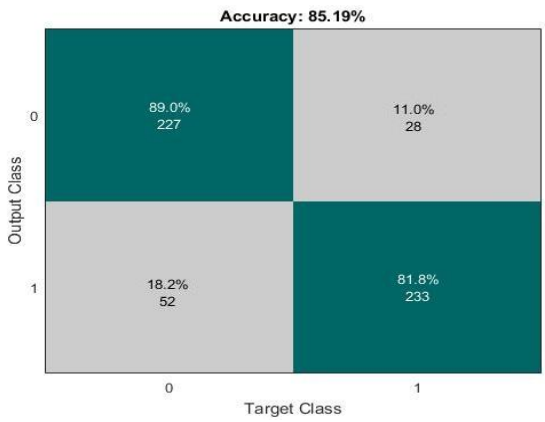

Fig. 15. Confusion matrix 540-540 dataset

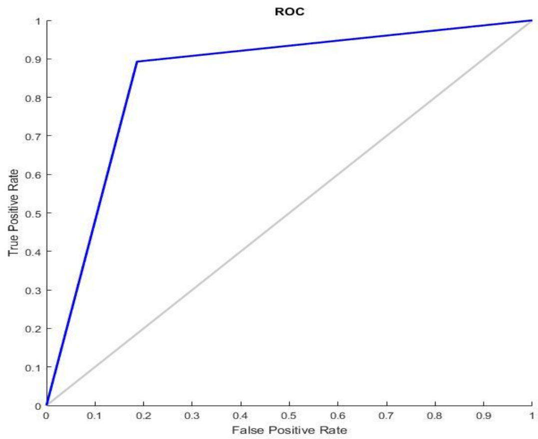

Fig. 16. ROC Curve 540-540 dataset

It can be concluded from fig. 15 prediction of forest fires that were classified correctly 85.19%.

3) 756 instances for training set and 324 instances for testing set.

Fig. 17. Confusion matrix 756-324 dataset

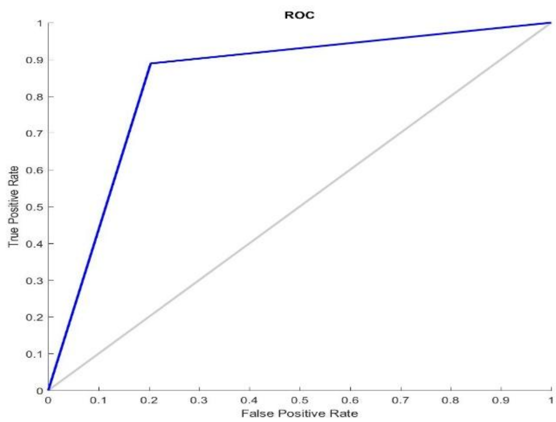

Fig. 18. ROC Curve 756-324 dataset

It can be concluded from fig. 17 prediction of forest fires that were classified correctly 84.26%.

TABLE III. SPECIFICITY AND SENSITIVITY USING SIGMOID ACTIVATION FUNCTION FOR DIFFERENT TRAINING AND TESTING PARTITION

Sample Datasets	*Specificity*	*Sensitivity*
648-432	87.28%	85.78%
540-540	89.27%	81.36%
756-324	88.89%	79.63%

D. Using SinC Function

1) 648 instances for training set and 432 instances for testing set.

Fig. 19. Confusion matrix 648-432 dataset

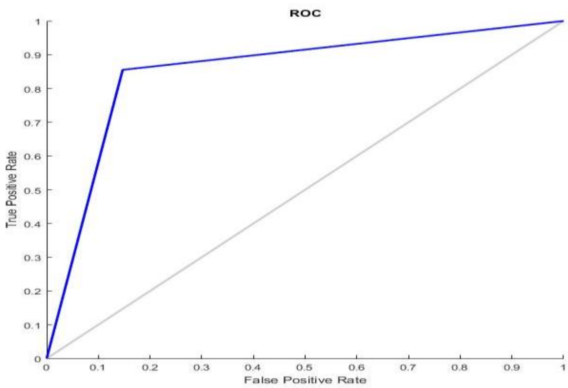

Fig. 20. ROC Curve 648-432 dataset

It can be concluded from fig. 19 prediction of forest fires that were classified correctly 85.42%.

2) 540 instances for training set and 540 instances for testing set.

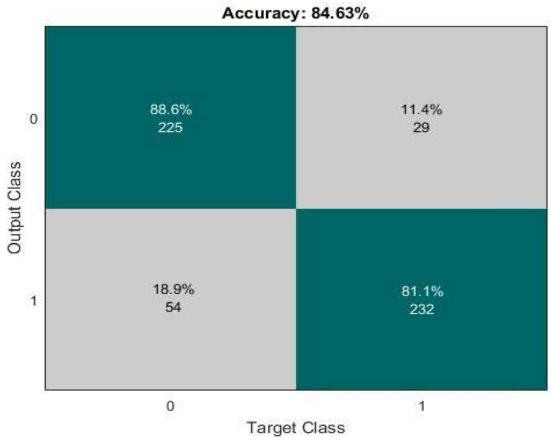

Fig. 21. Confusion matrix 540-540 dataset

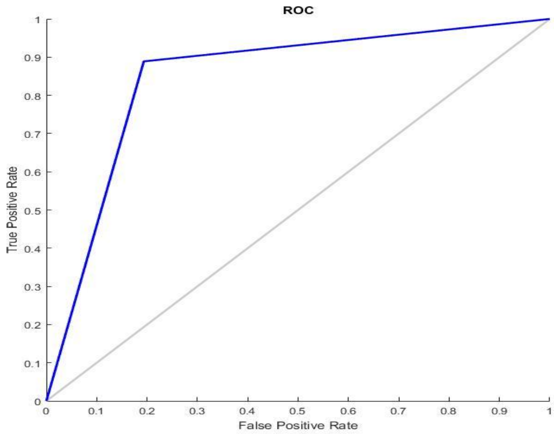

Fig. 22. ROC Curve 540-540 dataset

It can be concluded from fig. 21 prediction of forest fires that were classified correctly 84.63%.

3) 756 instances for training set and 324 instances for testing set.

Fig. 23. Confusion matrix 756-324 dataset

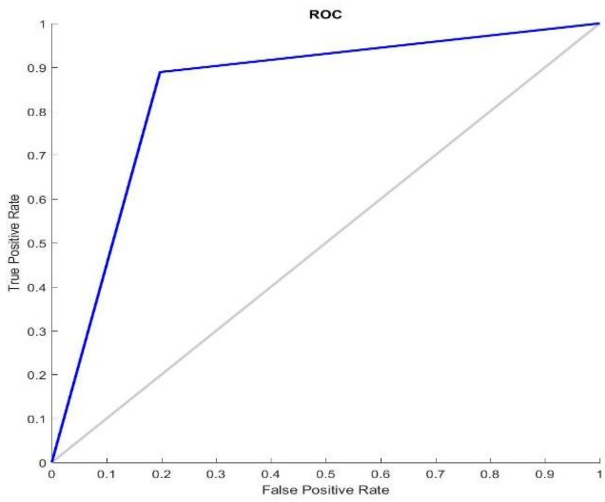

Fig. 24. ROC Curve 756-324 dataset

It can be concluded from fig. 13 prediction of forest fires that were classified correctly 84.57%.

TABLE IV. SPECIFICITY AND SENSITIVITY USING SINC ACTIVATION FUNCTION FOR DIFFERENT TRAINING AND TESTING PARTITION

Sample Datasets	*Specificity*	*Sensitivity*
648-432	85.53%	85.29%
540-540	88.89%	80.64%
756-324	88.89%	80.28%

E. Using Triangular BasisFunction

1) 648 instances for training set and 432 instances for testing set.

Fig. 25. Confusion matrix 648-432 dataset

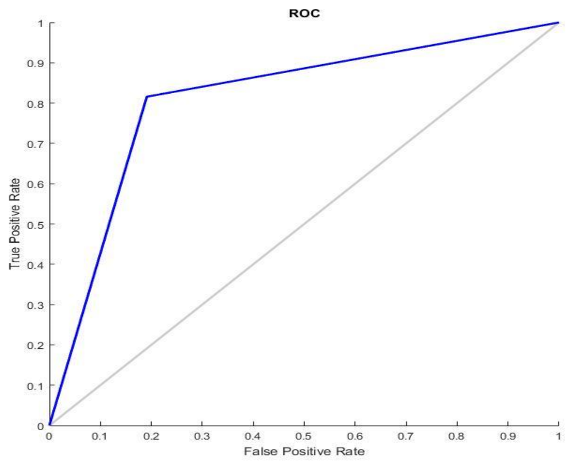

Fig. 26. ROC Curve 648-432 dataset

It can be concluded from fig. 25 prediction of forest fires that were classified correctly 81.25%.

2) 540 instances for training set and 540 instances for testing set.

Fig. 27. Confusion matrix 540-540 dataset

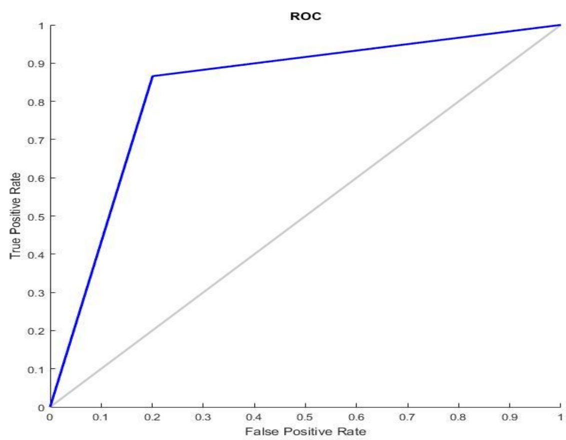

Fig. 28. ROC Curve 540-540 dataset

It can be concluded from fig. 27 prediction of forest fires that were classified correctly 83.15%.

3) 756 instances for training set and 324 instances for testing set.

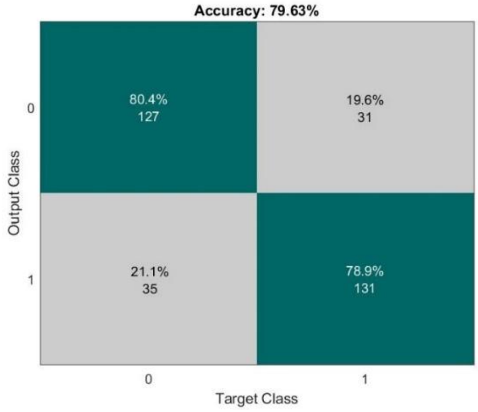

Fig. 29. Confusion matrix 756-324 dataset

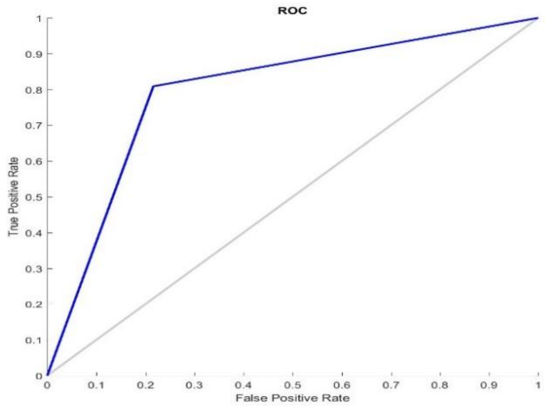

Fig. 30. ROC Curve 756-324 dataset

It can be concluded from fig. 29 prediction of forest fires that were classified correctly 79.63%.

TABLE V. SPECIFICITY AND SENSITIVITY USING TRIANGULAR BASIS ACTIVATION FUNCTION FOR DIFFERENT TRAINING AND TESTING PARTITION

Sample Datasets	*Specificity*	*Sensitivity*
648-432	81.58%	80.88%
540-540	86.59%	79.93%
756-324	80.86%	78.39%

TABLE VI. ACCURACY COMPARISON OF FIVE ACTIVATION FUNCTIONS

Sample Datasets	*Hardlim*	*Sigmoid*	*SinC*	*Radial Basis*	*Triangular Basis*
648-432	75.37%	85.19	84.63	84.81	83.15
540-540	77.08%	86.57	85.42	84.95	81.25
756-324	76.54%	84.26	84.57	83.64	79.63

The Table VI shows comparative analysis of presented framework with five different activation function. Results can be concluded as the algorithm performed best in case of 540 training instances and 540 testing instances. The best accuracies in this proposed framework is achieved by sigmoid activation function. It can be concluded that sigmoidactivation function is most appropriate for forest fire prediction.

V. CONCLUSION

Experiments are concluded for three partitions having different number of training set instances and testing set instances for forest fire Prediction. Results from experiments shows that best accuracy achieved from model trained with sigmoid activation function is fordataset having540 training instances and 540 testing instances, with SinC function it is 85.42%, with radial basis function it is 84.95%. However the accuracy decrease to 77.08% for the model trained with hardlim function. Results from the proposed work demonstrate that ELM classifiers trained with five different activation functions achieved maximum accuracy for dataset having 540 training instances and 540 testing instances. Results shows that sigmoid function outperformed other activation functions and hardlim function has most poor performance among the five activation function tested in case of 648-432, 540-540 and 756-324 training and testing instances respectively. With based on experimental results sigmoid activation function on all partition has better performance and suggested to be used further for forest fire prediction.

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