Deep Learning Neural Networks for Non-Linear Analysis of Combustion Quality Monitoring in Power Station Boilers

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Abstract

The combustion quality determination in power station boilers is of great importance so as to avoid air pollution. The emission of harmful gases as a result of incomplete or partial combustion can be reduced by monitoring the flame images at the furnace of the boiler. Complete combustion minimises the exit of NOx, SOx, CO and CO2 emissions also ensuring the consistency in load generation. If the combustion was complete then the flue gas emissions are maintained within minimum limits. Flame image analysis was done using Support Vector Machine (SVM) and classification based on the combustion quality was done with Meta Classification via Clustering, Cross Validation Parameter Selection (CVP), Radial Basis Function Network (RBFN) and MultiLayer Perceptron (MLP). Various performance measures are used for cross validation to estimate the combustion conditions. This research work is a combination of Fisher's linear discriminant analysis and radial basis function method for identifying the combustion conditions from the flame images of a boiler. The images in the control room are acquired using an infrared camera fixed to the inner portion of the boiler. The features of the image are further extracted using correlation. The dimensions of the input for the training patterns are reduced from 30 to 2 using optimal discriminant plane technique. Two projection vectors $\varphi 1$ and $\varphi 2$ is calculated for reducing the dimension of the input pattern. During training and testing of Radial Basis function Network (RBF), the number of input nodes is 2. Nineteen patterns have been used for training RBF and another 19 patterns for testing the RBF. Results obtained are promising and positive to implement for closed loop monitoring of the boiler.

Key words: Combustion quality, Support vector machine, Radial basis function network, Multilayer perceptron, Meta Classification via Clustering, CV Parameter Selection, intelligent technique, Automation.

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1. Introduction

The boilers are steam generators which convert pre-heated water into super heated steam. This high pressure super heated steam drives the turbine coupled to a generator which in turn generates power [1]. The Thermal Power Station (TPS) – Expansion-I at Neyveli (NLC) has two units with generation capacity of 210MW each. The total height of the boiler is 90m and the entire firing process gets over within 42m. The furnace is located at the 18th metre of the boiler. The heavy oil is used for initial firing and thereafter the firing process is enhanced by using lignite as the fuel whose calorific value is 2350 kCal/kg and fired at a rate of 189 to 230 t/hr. The firing system is called as tangential firing system. It includes six mills to crush the coal so that it becomes fine powder. The coal is also pre-heated so that it is used as the pulverized coal. The figure for tangential firing system is shown in figure 1 below.

1.1 Existing Vs Proposed flame monitoring system

The existing set-up at NLC has an infra-red camera placed inside a water-cooled jacket with servo-motor mechanism for retracting the same. The video captured by the camera is displayed on the CRT monitor is used for identifying the presence or absence of the flame to avoid explosion of the boiler [8]. The repeated loading of the furnace without monitoring the flame status causes explosion of the boiler which is very dangerous [5, 4]. The figure 2a shows the block diagram for the existing set-up at NLC. In the proposed system shown in figure 2b includes an additional device for transferring the video from the CRT monitor onto the laptop with various image processing algorithms. The video was splitted into frames these frames where further analyzed for the same.

2. Materials and Methods

2.1. Fisher's Linear Discriminant Function (FLD)

The process of changing the dimensions of a vector is called transformation. The transformation of a set of n-dimensional real vectors onto a plane is called a mapping operation. The result of this operation is a planar display. The main advantage of the planar display is that the distribution of the original patterns of higher dimensions (more than two dimensions) can be seen on a two-dimensional graph. The mapping operation can be linear or non-linear. R.A. Fisher developed a linear classification algorithm [1] and a method for constructing a classifier on the optimal discriminant plane, with minimum distance criterion for multi-class classification with small number of patterns [2]. The method of considering the number of patterns and feature size [3], and the relations between discriminant analysis and multilayer perceptron has been addressed earlier. A linear mapping is used to map an n-dimensional vector space $\mathfrak{R}^n$ onto a two-dimensional space. Some of the linear mapping algorithms are principal component mapping, generalized de-clustering mapping, least squared error mapping and projection pursuit mapping. In this paper, the generalized de-clustering optimal discriminant plane is used.

2.2. Radial basis function Network (RBFN)

A neural network is constructed by highly interconnected processing units (nodes or neurons) which perform simple mathematical operations. Neural networks are characterized by their topologies, weight vectors and activation function which are used in the hidden layers and output layer [4]. The topology refers to the number of hidden layers and connection between nodes in the hidden layers. The activation functions that can be used are sigmoid, hyperbolic tangent and sine. The network models can be static or dynamic. Static networks include single layer perceptron and multilayer perceptron. A perceptron or adaptive linear element (ADALINE) refers to a computing unit [5-6]. This forms the basic building block for neural networks. The input to a perceptron is the summation of input pattern vectors by weight vectors.

Information flows in a feed-forward manner from input layer to the output layer through hidden layers. The number of nodes in the input layer and output layer are fixed. It depends upon the number of input variables and the number of output variables in a pattern. In this application, the network parameters suchas the number of nodes in the hidden layer and the number of hidden layers are found by trial-and-error method. In most of the applications one hidden layer is sufficient.

The Radial Basis function (RBF) network (Figure 1) is a feed forward neural network with input layer, hidden layer and output layer. It is a real valued function [7], whose value depends only on the distance. The nodes of the hidden layer use an activation function f(x) = exp(-x) which varies monotonically with respective to the distance from the centre. The activation function is used to develop RBF output in each node in the hidden layer. A bias value of '1' is also used. The input to the activation function is the modulus of distance between the input pattern and the mean centre of patterns. The centres should be chosen such that all the patterns in a group cluster around the respective centres. When the centres are not chosen properly then the results may not be promising. Hence, a rule of thumb can be used to find centre as the mean of each class. If the classes are considered, then mean for each class can be used as centre to find distance among input patterns and the centres.

2.3. Procedure for Data Collection

The flame images corresponding to three different combustion conditions were collected by varying the air/fuel ratio and taking the corresponding readings of flame temperature, NOx, SOx, CO and CO2 emissions [3, 2]. The sample images corresponding to the above said three categories (shown in figure 3) with their respective parameters are tabulated in the table 1 below.

2.4. Pre-Processing

The images extracted are pre-processed for removal of noise. The noise removal is done with a median filter. The size of each frame is 320x240. A square image of 240x240 is taken into consideration for further processing Histogram analysis was done to identify the range of intensities corresponding to each group as shown in figure 4 below. The colour flame images are converted into gray scale images using threshold-based edge detection technique.

2.5. Feature Extraction

The features denote the basic pattern of an image that gets repeated in various directions. The features like orientation, centroid, area, area through equation, average intensity etc., are extracted from the image using Matlab. The extracted features are normalized to reduce computational complexity.

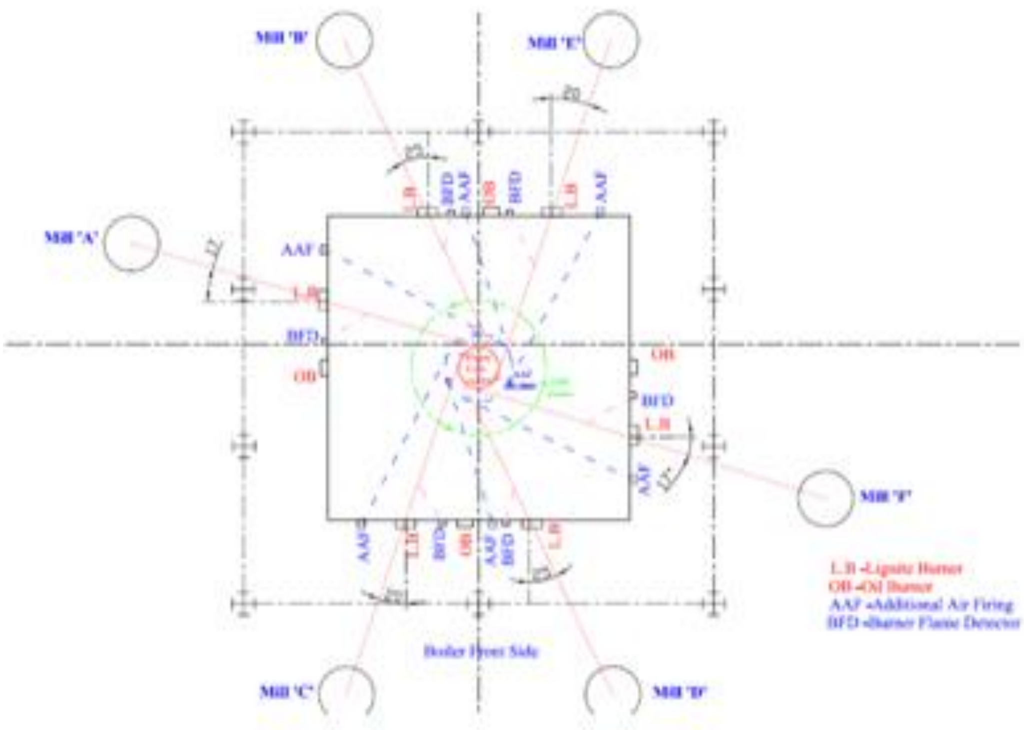


Figure 1. Tangential firing system

2.6. Feature Reduction

The features are reduced using SVM technique. Support vector machines (SVMs) are a set of related supervised learning methods used for classification. Intuitively, an SVM model is a representation of the points in space, mapped so that the features of the separate categories are divided by a clear gap that is as wide as possible. New features are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on. Support vector machine constructs a hyper plane or set of hyper planes in a high or infinite dimensional space, which can be used for classification tasks. Here the attributes are ranked by the SVM technique [7]. The results obtained by SVM feature reduction and the screen shots are shown in figure 5and its variation during classification are exhibited in Figure 6 (a) to (f). The ranking of the features by SVM are given in table 2 below.

Table 1(a). Measurement of parameters corresponding to each group of images

Class	NOx mg/Nm3	CO ppm	CO2 Nm3/hr	SOx Nm3/hr
1	70	100 to 120	1000	70
2	120	200 to 210	3000	120
3	200	300	7000	200

Table 1(b). Measurement of parameters corresponding to each group of images

Combustion conditions	Flame Temperature in (deg Celsius)	Air/fuel ratio (No units)
Complete	1250	Ratio is 4:1, 890 t/hr-air, 182 t/hr- lignite
Partial Combustion	900	Ratio is 3:1, 600 t/hr – air, 213 t/hr- lignite
Incomplete Combustion	300	Ratio is 2:1, 230 t/hr- lignite, 400 t/hr - air

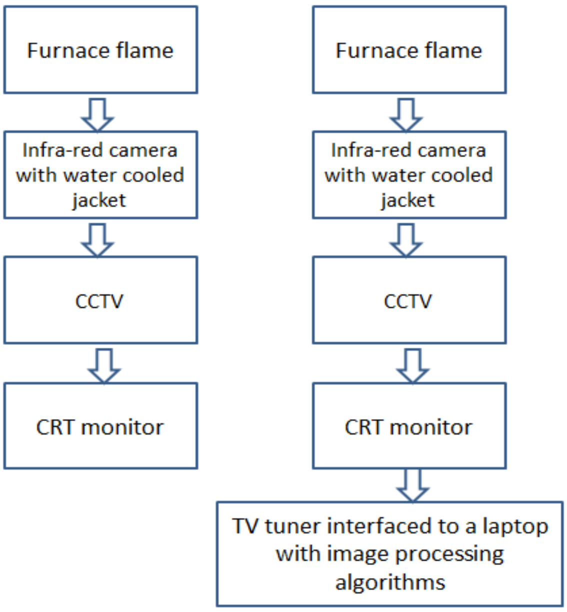


Figure 2. Existing Vs Proposed Set up

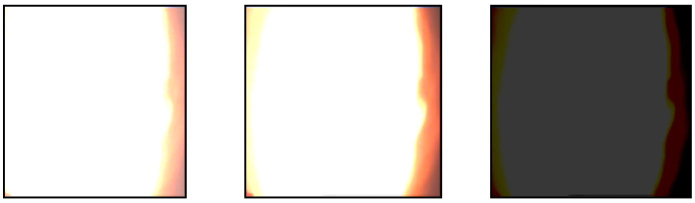
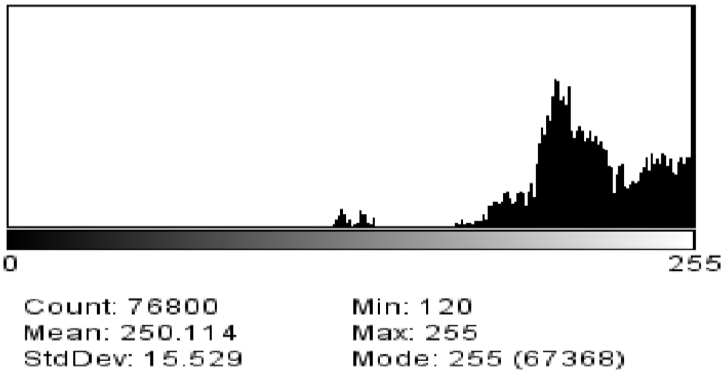
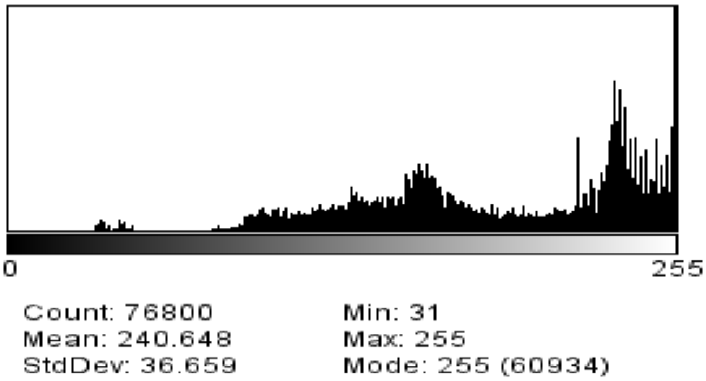


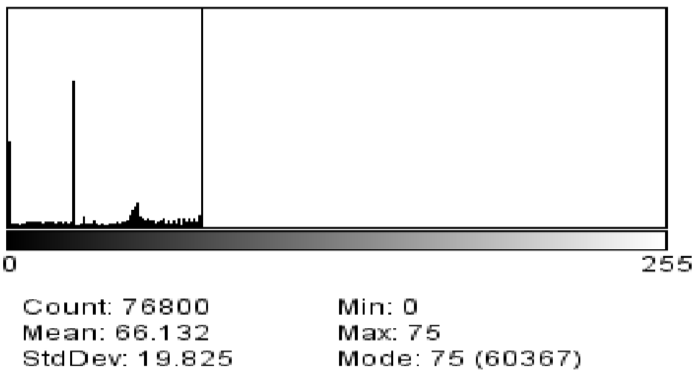
Figure 3. Flame images-complete, partial and incomplete combustion



a) Complete combustion



b) Partial combustion



c) Incomplete combustion

Figure 4. Histogram Analysis for flame images

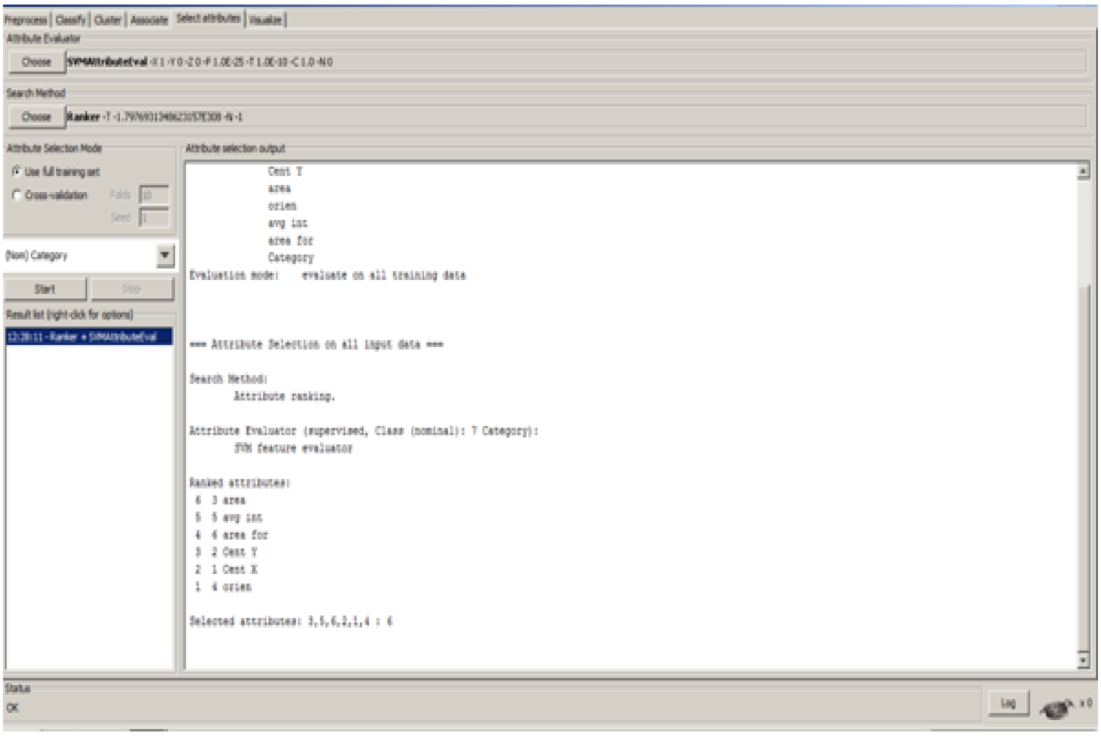


Figure 5. Screen shot for feature ranking by SVM

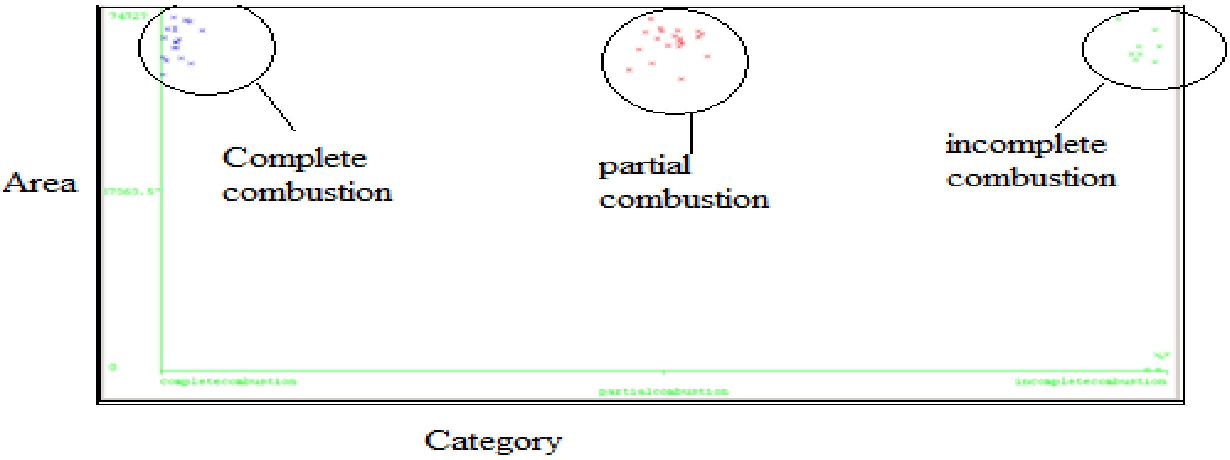
Table 2. Ranking the features using SVM

S.No	List of the Features extracted	Position of attributes as ranked by SVM
1.	Centroid about X	2nd Position
2.	Centroid about Y	3rd Position
3.	Area	6th Position
4.	Orientation	1st Position
5.	Average Intensity	5th Position
6.	Area through equation	4th Position

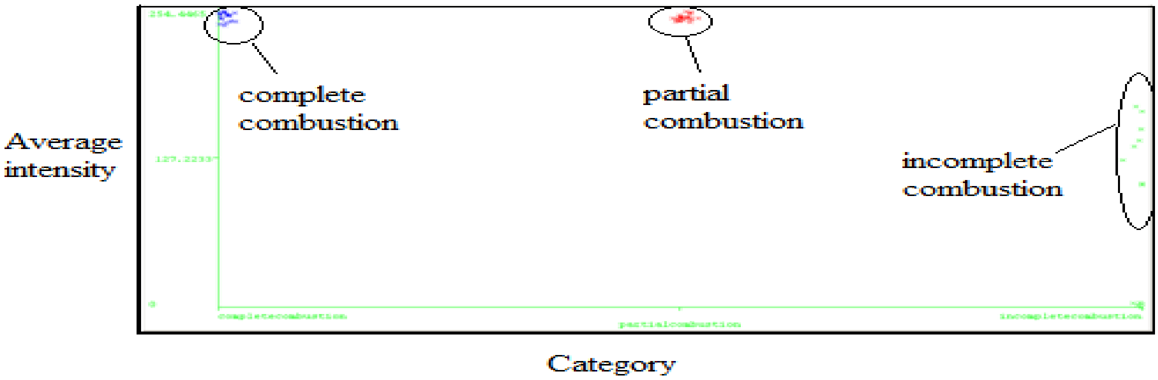
2.7. Classification

2.7.1. Radial Basis Function Network (RBFN)

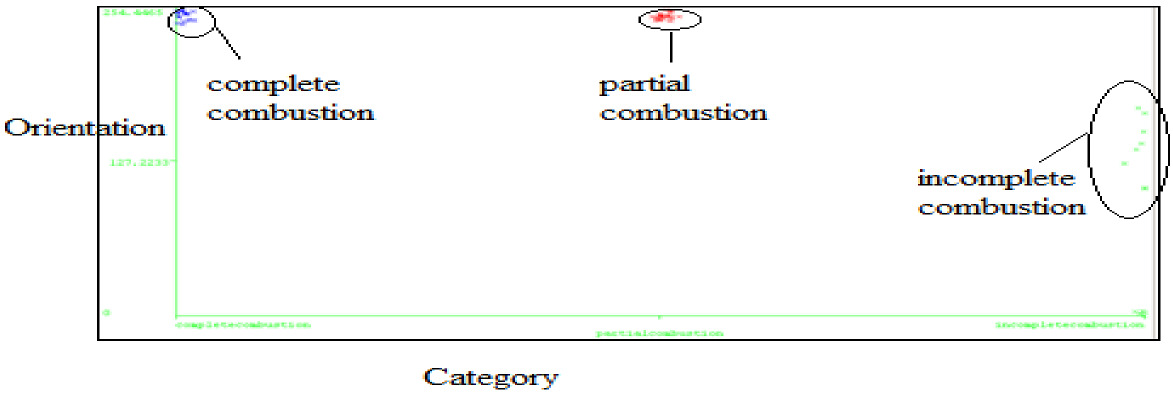
The intelligent classifier [6] used is a Radial Basis Function Network (RBFN). The Radial Basis function (RBN) network is a feed forward neural network with input layer, hidden layer and output layer. Centres are created from the training data. The distance between training pattern and the centres are found. The output of hidden layer is obtained by using the Gaussian function. A bias value of '1' is used for matrix multiplication. The input to the activation function is the modulus of distance between the input pattern and the mean centre of patterns. The centres should be chosen such that all the patterns in a group are around the respective centres. Hence, a rule of thumb can be used to find the centre as the mean of each class, the distance among input patterns and the centres [3, 8].


Area
Complete combustion
partial combustion
incomplete combustion
Category

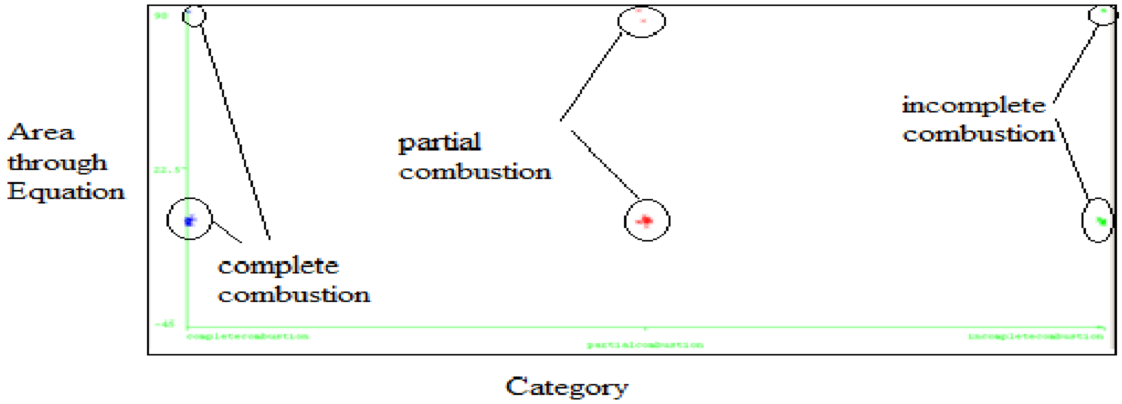
(a).


Average intensity
complete combustion
partial combustion
incomplete combustion
Category

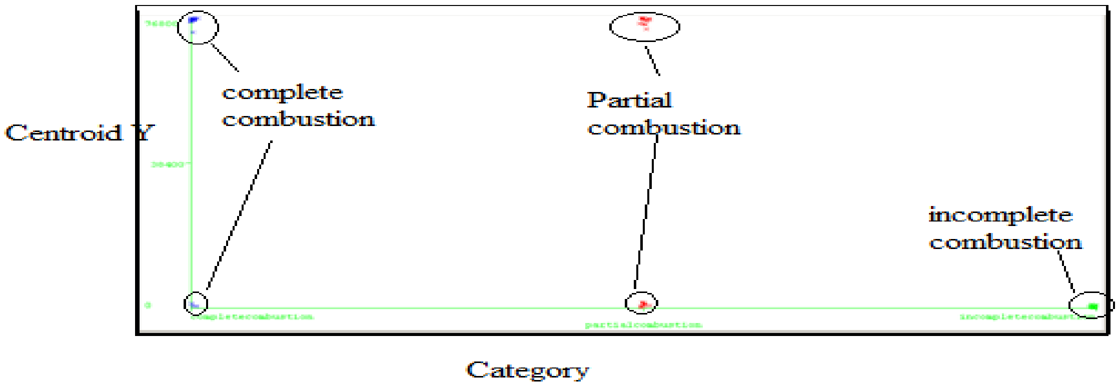
(b)


Orientation
complete combustion
partial combustion
incomplete combustion
Category

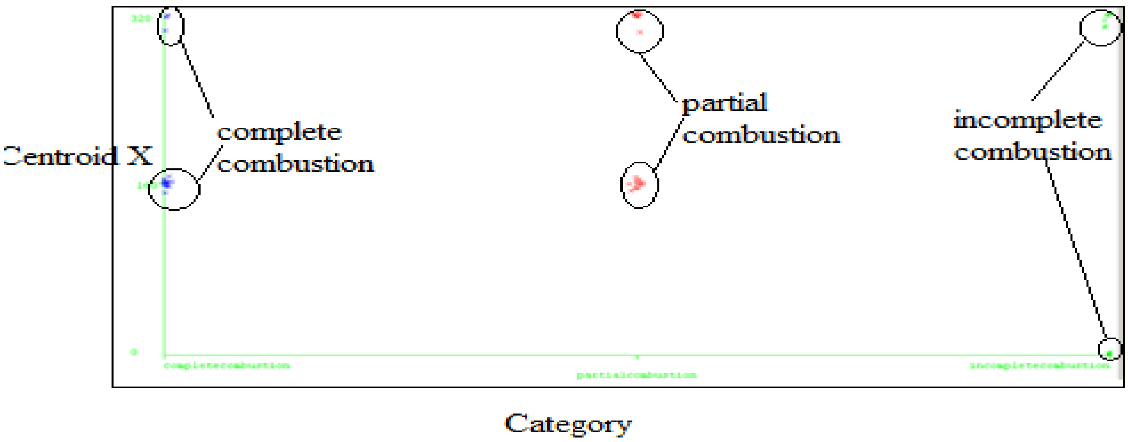
(c).



(d).



(e).



(f).

Figure 6. Variation of the features-Category by SVM feature reduction

2.7.2. Multilayer Perceptron (MLP)

Another type of intelligent classifier called Multilayer perceptron (MLP) classifier was also used for inferring combustion quality in power station boilers [9]. The MLP has three layers namely the input layer, hidden layer and the output layer. The activation function used is a sigmoid function. The number of nodes in the input layer is six, number of nodes in the hidden layer is twenty and that in the output layer are three to identify the combustion quality. The mean squared error is the objective function [6, 9].

2.7.3. Meta Classification via Clustering

Various classification and clustering algorithms became available due to a surge of interdisciplinary research interests in the areas of data mining and knowledge discovery. We develop a statistical meta-model which compares the classification performances of several algorithms in terms of data characteristics. This empirical model is expected to aid decision making processes of finding the best classification tool in the sense of providing the minimum classification error among alternatives. Concepts and algorithms of feature selection, surveys existing feature selection algorithms for classification and clustering, groups and compares different algorithms with a categorizing framework based on search strategies, evaluation criteria, and data mining tasks, reveals unattempt combinations, and provides guidelines in selecting feature selection algorithms. With the categorizing framework, we continue our efforts toward building an integrated system for intelligent feature selection.

2.7.4. Cross Validation Parameter (CVP) Selection

Cross-validation is determined by holding all of the model parameters, γ = {β, σˆ 2 ,θ}, constant while creating n models using each subset of the remaining n-1 points, and calculating the error at each omitted location in turn. Computationally an efficient formula can be used for the "leave-one out" CV error of prediction at the deleted site for a constant trend function in the model. The q is the inverse of the diagonal of R−1. The elements of q are placed on the diagonal of a matrix Q, allowing the cross-validation of a more complex trend function. By minimizing the average squared bias, the estimated values of trend function coefficients are found out, where Q2 is QTQ , or Q with each element squared. Minimized over the correlation function parameter space by substituting the optimal β, which is a function of the correlation function parameters. This method is similar to the profile log-likelihood method to reduce the number of variables to be optimized. An advantage to CV is that it does not assume any probability distribution shape for the observations, which may result in a better estimate of the optimal model parameters [10].

3. Results and Discussion

The flame images are obtained from the control room of the thermal power plant boiler. The image is preprocessed to make sure that correct image is used for analysis and monitoring purposes. The group 1 and group2 images have been considered for training and testing of RBF as shown in Table 1. From each group nearly 50% of images have been considered for training and 50% of images have been considered for testing. Each image is processed and a suitable square matrix of the image is considered after experimenting for various combinations. Step 1 to step 7 outputs 30 values as shown in Table 2 as the size of the image cropped is 30 x 30 from the actual size 47 x 35 acquired.

3.1. Training of RBFN, MLP, Classification via Clustering and CVP algorithms

Totally 39 images were taken for training. 39 images, includes images obtained under complete combustion, partial combustion, incomplete combustion conditions along with NOx, CO_2, CO and SOx emissions. According to the ranking of the features, if the feature 4 and feature 1 alone are considered for training, the Root Mean Squared Error (RMSE) is 0.3908 and if the features 4,1,2,6 are considered for training the RMSE was 0.3358 along with meta classification via clustering and CVP algorithms as shown in Figure 7(a), (b), (c) and (d). Hence features 4,1,2,6 is considered for testing of the RBFN.

```
Incorrectly Classified Instances         0               0      %
Kappa statistic                          1
Mean absolute error                      0.019
Root mean squared error                  0.0377
Relative absolute error                  4.2803 %
Root relative squared error              7.9877 %
Total Number of Instances               39

=== Detailed Accuracy By Class ===

               TP Rate   FP Rate   Precision   Recall  F-Measure   ROC
                 1         0          1          1        1          1
                 1         0          1          1        1          1
                 1         0          1          1        1          1
Weighted Avg.    1         0          1          1        1          1

=== Confusion Matrix ===

  a  b  c   <-- classified as
 13  0  0 |  a = complete combustion
  0 13  0 |  b = incomplete combustion
  0  0 13 |  c = partial combustion
```

(a). Training by RBFN

```
Kappa statistic                          1
Mean absolute error                      0
Root mean squared error                  0
Relative absolute error                  0      %
Root relative squared error              0      %
Total Number of Instances               39

=== Detailed Accuracy By Class ===

               TP Rate   FP Rate   Precision   Recall  F-Measure   ROC
                 1         0          1          1        1          1
                 1         0          1          1        1          1
                 1         0          1          1        1          1
Weighted Avg.    1         0          1          1        1          1

=== Confusion Matrix ===

  a  b  c   <-- classified as
 13  0  0 |  a = complete combustion
  0 13  0 |  b = incomplete combustion
  0  0 13 |  c = partial combustion
```

```
Incorrectly Classified Instances        13              33.3333 %
Kappa statistic                          0.5
Mean absolute error                      0.2222
Root mean squared error                  0.4714
Relative absolute error                 50      %
Root relative squared error            100      %
Total Number of Instances               39

=== Detailed Accuracy By Class ===

               TP Rate   FP Rate   Precision   Recall  F-Measure   ROC Area
                 1         0          1          1        1          1
                 0         0          0          0        0          0.5
                 1         0.5        0.5        1        0.667      0.75
Weighted Avg.    0.667     0.167      0.5        0.667    0.556      0.75

=== Confusion Matrix ===

  a  b  c   <-- classified as
 13  0  0 |  a = seventy mg/nominal cubic metre
  0  0 13 |  b = hundred and twenty mg/nomial cubic metre
  0  0 13 |  c = two hundred mg/nomial cubic metre
```

(c). Training by Meta classification via clustering

```
Incorrectly Classified Instances        26               66.6667 %
Kappa statistic                          0
Mean absolute error                      0.4444
Root mean squared error                  0.4714
Relative absolute error                100      %
Root relative squared error            100      %
Total Number of Instances               39

=== Detailed Accuracy By Class ===

               TP Rate   FP Rate   Precision   Recall  F-Measure   ROC Area
                 1         1         0.333      1        0.5         0.5
                 0         0         0          0        0           0.5
                 0         0         0          0        0           0.5
Weighted Avg.    0.333     0.333     0.111      0.333    0.167       0.5

=== Confusion Matrix ===

  a  b  c   <-- classified as
 13  0  0 |  a = complete combustion
 13  0  0 |  b = incomplete combustion
 13  0  0 |  c = partial combustion
```

(d). Training by CVP

Figure 7 Screen shots for training by various algorithms for temperature estimation

3.2. Testing of RBFN, MLP, Classification via Clustering and CVP Algorithms

The testing was done and the results are also validated. Totally 39 images were taken for testing. The values of True Positive (TP), Recall and Precision are ‘1’ for the classification by the RBFN and MLP networks. On the other hand, the values of False Positive (FP) are ‘0’ is shown in figures 8, 9, 10 and 11 below. The comparison chart in figure 12 shows that the images were classified based on their combustion quality, NOx, CO2, CO and SOx emissions by SVM feature analysis. The TP, recall and precision values are nearly ‘1’for all the three categories by RBFN and MLP classifier.

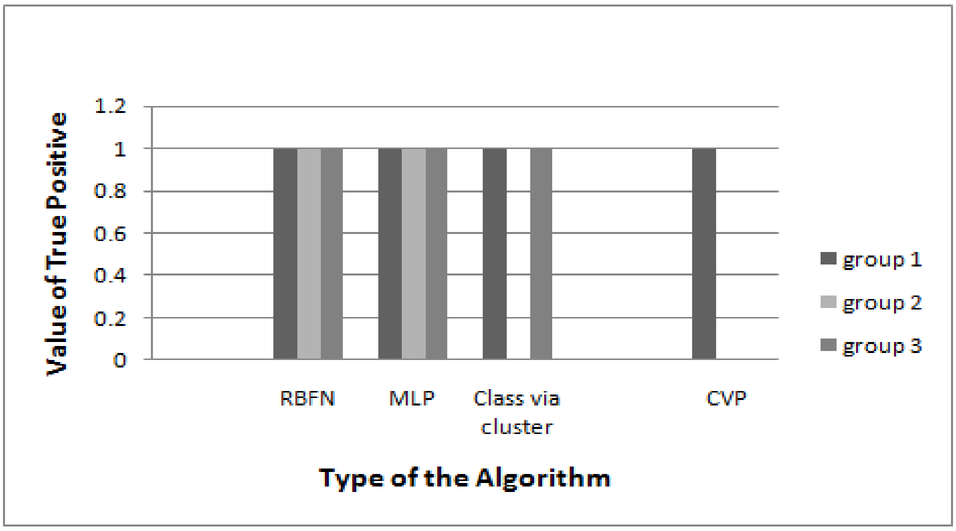


Figure 8. True Positive for various algorithms during testing

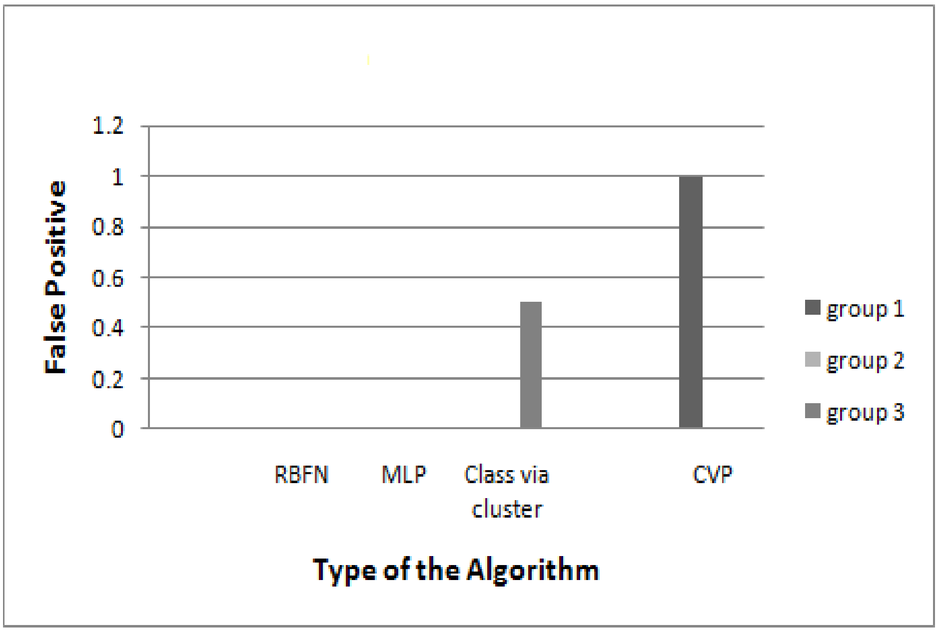


Figure 9. False Positive for various algorithms during testing

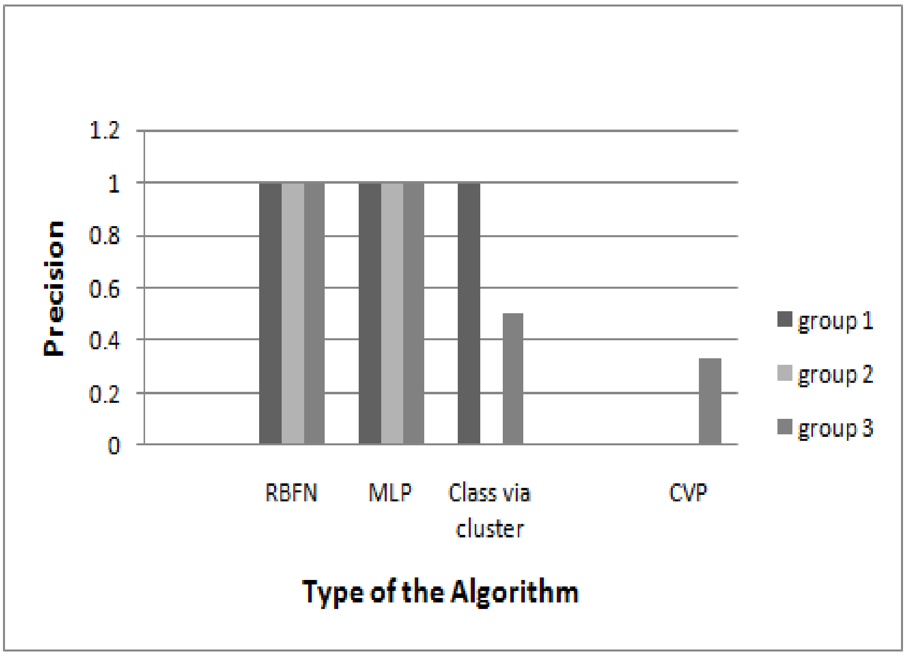


Figure 10. Precision for various algorithms during testing

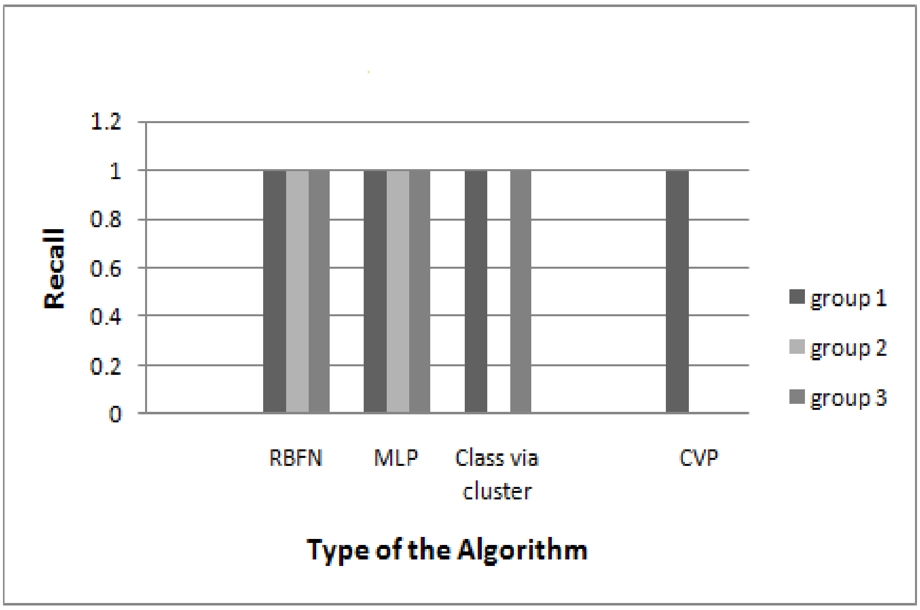


Figure 11. Recall for various algorithms during testing

Table 3. Distribution of images for training and testing RBF

Group	**Number of images for training**	**Number of images for testing**
1	10	9
2	10	9
Total	20	18

The φ1 and φ2 vectors obtained after processing the 38 images from group 1 and group 2 are given in Table 3. The centres are calculated based on the 2D vector of all the 40. The triangular points show group 2 and square points represent group 1. The common centre for group 2 and group 1 are indicated. The distance between these two common centres are large and ther is no overlapping of centres from either group, that indicates, the images of complete combustion and incomplete combustion are distinct. By the process of FLD, φ_1 and φ_2 discriminant vectors are obtained by using three flame images. RBF is trained with 2D vector formed by processing φ_1 and φ_2 with the eigenvector of images. A set of final weights are obtained by training RBF with desired target values. Testing of image to know the complete combustion or incomplete combustion is done with final weights obtained. Testing results indicate only 31 images were correctly classified out of 38 images which indicate 81.58 % classification.

4. Conclusion

Thus, the automation of combustion quality was done by analysing the flame images for a power station boiler. The features were extracted and reduced using SVM technique and classified by using RBFN, MLP, and Classification via Clustering and CVP algorithms. The True Positive (TP) for RBFN and MLP is '1' for all the three categories of combustion whereas for the other two algorithms the TP value is '0'. The False Positive (FP) for RBFN and MLP is '0' whereas for the other algorithms it has the maximum value. The precision and recall values for all the three categories by RBFN and MLP is '1' whereas for the other algorithms it is very much less than 1 or even '0' nearly. This states that monitoring and control of combustion quality in power station boilers can be done successfully using intelligent techniques like SVM based feature reduction with RBFN and MLP classification. In this work, sixty flame images were collected from the control room of boiler and forty correct images were identified. Fisher's linear discriminant function is used to transform image into 2D vector. Training of RBF was done with 38 images. Testing results indicate only 31 images were correctly classified out of 38 images which indicate 81.58 % classification. Classification performance can be further improved by further preprocessing of the acquired images.

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