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Prediction of Oxygen Content using Deep Learning CNN Architecture for the Classification of Blast Furnace Gas Fired Boiler Images

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Abstract: **Prediction of oxygen content in a combustion process is one of the prime and arduous task. As high temperatures are involved, there are seldom any equipment available, that can be placed inside the furnace to make measurements. to obliviate this problem, in this work, a convolution neural network (CNN) is applied to an industrial process of furnace combustion. Flame images of a working gas fired boiler are obtained by a high definition camera and an artificial neural network, CNN is applied to anticipate the oxygen content present in flue gas of a BFG gas fired boiler. A multilayer CNN model is used to describe better, the key patterns in a combustion process by extracting the non-linear aspects. Using a CNN model and a multilayer representation of the CCD flame pictures, more in-sightful data regarding the physical characteristics of flames can be defined. This concept is applied to flame images obtained on-site from a real combustion system. The loss obtained is 0.04, quite a low value, after the model training, and acquired 97% accuracy, which is very good for classification tasks during testing.**

Keywords: BFG Gas Boiler, Image Analysis, CNN Classification, Python PiTorch Framework, O_2 Prediction.

I. Introduction

Efficiency of a boiler in the combustion of fuel is an important strategy and the aim of the process is to save the fuel and reduce heat losses in flue gases [1]. Control of fuel combustion in an automatic process increases efficiency of a boiler, as well, brings reduction of harmful emission of carbon monoxide, nitrous oxide, hydrogen etc [2, 3], in the atmosphere. Hardware based analysis used in the industrial processes has the disadvantage that maintenance, purchase cost of oxygen analyzer are high and another disadvantage is that measurement delay is present in online surveilling and regulation of the combustion process [4]. Temperatures of a furnace are the key indices of a combustion process. Temperature monitoring is usually done at typical locations and an overall value cannot be obtained by such measurements, on the other hand optical and laser measurements are very costly and it is a very tough job to accurately place the instrument and do the maintenance on regular basis [5]. Prediction of oxygen is a challenging task. By using digital image processing, current monitoring of live flame images can be done in a cost effective manner [6]. Using high definition flame images acquired by Charge Coupled Devices(CCD) and a grabber of flames, the images are digitized [7]. It was suggested by Yan et al [6], to observe the flame's temperature distribution in a gasified state. Draper et al., developed a method based on images to gauge the temperature of the coal flame and total emissivity. Gonzalez-Cencerrado et al [8], used image processing and flame visualization to describe a combustion state. Yi Liu proposed a method using flame shots to indicate the presence of oxygen in combustion with the aid of Deep Belief Network method [9]. Multivariable analysis can also be performed for the internal process [10]. Reducing fuel consumption, increasing boiler efficiency as well as reducing harmful gases is a big challenge nowadays in a Blast Furnace Gas fired boiler(BFG). Flue gas temperature that is fed to atmosphere is around 175 to 190 ° C. In this effluent, a significant amount of energy is entailed due to which efficiency of thermal energy is very low , approx 86% [11]. Further, by using condensation, heat recovery in boiler flue gases can improve thermal efficiency [12]. This fact shows that new techniques and technologies must be looked for in order to optimize boiler operation [13]. One of the prominent causes of the boiler's low efficiency is, the loss of heat due to various reasons viz., chemical composition, external exhaust cooling, mechanical combustion, slag etc. In all the above, efficiency will increase by the method of heat recovery and it is an ecological aspect of burning carbon fuel [14]. When burning natural gas, biomass, and other fuels, authors have demonstrated in the literature that the amount and composition of flue gases are influenced by the excess air fuel ratio value. Additionally, techniques and tools for heat and power equipment quality control are actively being developed [15]. In combustion process, ANN using CNN technique is very rarely applied. The development of a CNN soft sensor system for a real-time combustion process quality prediction, is being attempted for the first time in this research [16]. By using ANN, such problems can be resolved that can bring about reduction in the losses and escalate efficiency of the system [17]. The brief explanation regarding ANN and CNN is given in the sections II and III. Blast Furnace Gas (BFG) Fired Boiler Combustion System is described in section IV. Methodology is delineated in section V followed by description of CNN Method and data Processing stage in section VI. In Section VII implementation of the proposed method and results are discussed. Last section is the concluding part.

II. Artificial Neural Network

Artificial Neural Network is a model in machine learning, utilized for classification and prediction of tasks. Similar to the human brain, it is made up of neurons that can be trained to recognize patterns for classification and prediction. Three layers make up the neural network: input, hidden layer, and output layer. Binary judgement, and collection of decisions through neural network and perceptrons is an effective research activity. So, an input is taken by a perceptron, which then finds the weighted sum, adds a bias and passes on through an activation function, to induce non linearity which helps the network to learn complex patterns. If the output of a neuron is above a certain threshold, then only it fires and passes on information to the neurons in subsequent layers. The force used in each input is learnt by the neural network at each neuron which helps the network to execute the specified task. During training, the network is loaded with random weights and it learns the weights needed to represent the training data distribution by fitting in it. The network propagates the weights in forward direction and compares the output with the actual, then, to minimize the error the network back propagates taking the same path and changing the weights using gradient descent such that error in anticipations made by the network is minimized at each of the traversed neuron. This is done until the network is able to predict the task. The prime ANN application is classification [18].

Working of ANN

- The input is divided into number of neurons to form an input layer.
- The input x is then passed to the next hidden layer which has an assigned default weight.
- The weight added indicates which input is impactful in the output.
$$F = w^T x + b \tag{1}$$
- After passing through all hidden layers, an output is obtained, which is compared to the true output
- Next, the loss function is calculated and the error is back propagated to update the weights of all neurons in hidden layers.
- The main aim is to upgrade the weights to an extent until loss function or cost function is minimum [19].

III. Convolution Neural Network

Image classification in a neural network is performed by CNN architecture. Comparatively, a CNN requires substantially less pre-processing than the other classification methods. CNN employs a variety of tailored filters, and with sufficient practice, CNN is able to pick them up. CNN has 3 layers namely

- convolution layer
- pooling layer
- completely connected layer

In the convolution layer, different filters are applied to find patterns like edge, intensity of different colors, etc. After the convolution layer, nonlinearity is induced using a typical activation function, the rectified linear unit (ReLu)function. The dominant features are found by Max pooling, which are rotational and positional invariant which aid to reduce dimensions of the image too, as max or min or average is taken on a patch of the input. Next, the fully connected layer gets the attribute vector, as the input maps the features to the output and then classifies [18].

Working of CNN

- The input is divided into various parts and sent into neurons for preprocessing.
- In order to filter the data and create a feature map; convolution is applied to the input layer.
- Activation Function is now applied like ReLu, Softmax, etc which perform element-wise operations and rectify feature map.
- A pooling layer is sometimes added which reduces the dimensionality of the input.
- Flattening is done at last layer that converts 2D arrays into single long continuous linear vectors.
- The output after flattening serves as an input for the totally connected layers for classification.

All these layers are optional and added as per the demand of input and output. By prediction of oxygen using CNN, efficient combustion can be acquired [19].

IV. Blast Furnace Gas (BFG) Fired Boiler Combustion System

In this system air and fuel from a blast furnace are obtained and used as a fuel injector in a boiler system. The emission level and combustion effectiveness should be managed

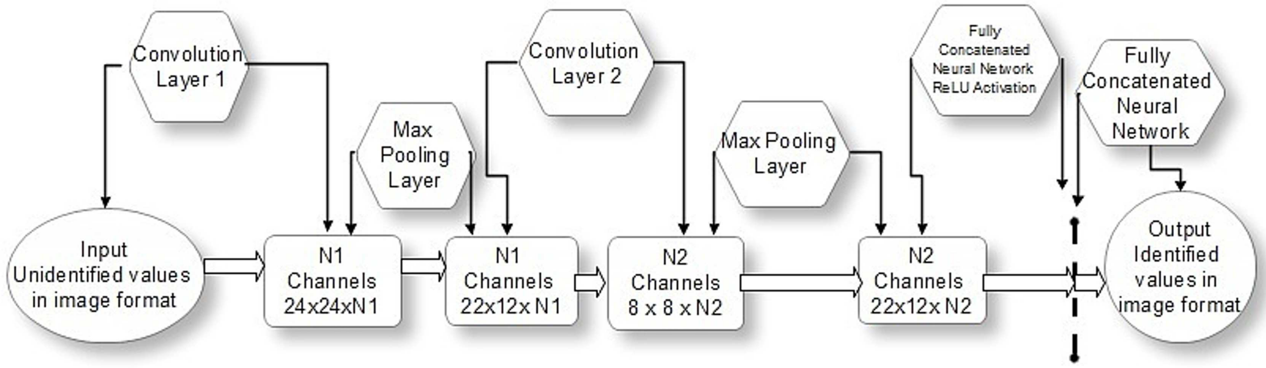


Figure. 1: Architecture of ANN [20]

at an appropriate level to save operating costs and comply with environmental standards. The use of gas analyzers for oxygen level measurement and NO_x quantity in exhaust gas will, however be delayed. In such a case, a feedback controller based on oxygen content has a propensity to compensate excessively. Online-measured flame pictures, as an alternative, can convey adequate details to depict the current status of combustion. As a result, flame image-based monitoring and control systems have recently attracted a lot of research interest [21, 22, 23]. Existing method is depicted

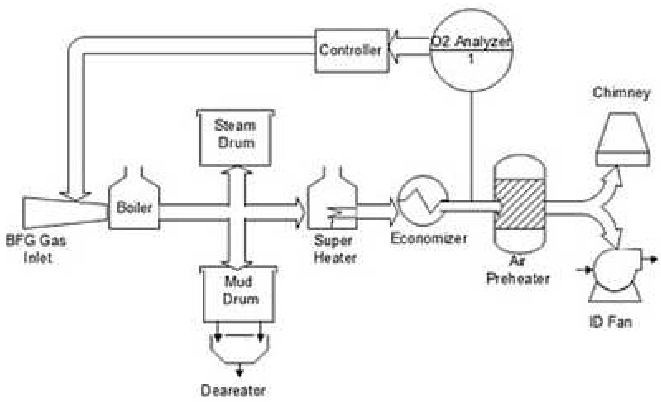


Figure. 2: Block Diagram of BFG Gas Fired Boiler

in block diagram as shown in Figure 2. Figure 3 shows a practical combustion system in which the furnace wall is prepared and covered with a fiber cotton, to ignite the furnace heavy oil & LPG Gas is used as a fuel initially, and then blast furnace fuel is utilized as a boiler fuel. The air for combustion is delivered by a direct-drive variable frequency fan with a maximum load of 21600 m^3/hr in a gas-fired boiler. A gas analyzer records the concentration of O_2, CO, and NO_x in exhaust gases[24]. A SCADA system automatically measures all variables of the process, like temperature, pressure, fuel gas and air flow rate[25]. The photographs of the flames in the furnace were captured with a digital color camera. A protective shield like cooling mechanism is equipped with CCD camera that will protect from high temperature, to avoid damage and also quality of image is maintained. Additionally, to avoid colour saturation, a number of optical filters are attached to the camera anteriorly[26, 27]. An

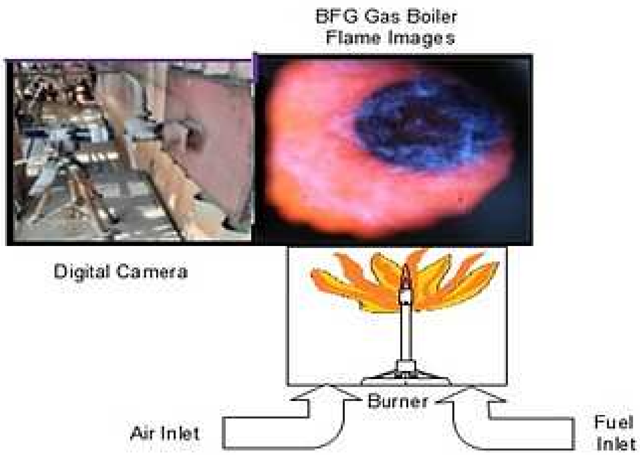


Figure. 3: Online flame Image Monitoring

IEEE-1394a interface is used to share acquired information to a PC. Each flame image in the test has 24 bits per pixel resolution and a size of 658×492 pixels. The photos are captured at a rate of one frame every five seconds.

A. Why Classification Method was chosen over prediction model?

The Gas-Fired Boiler Combustion Systems oxygen level lies in the range of 2.9 to 3.7, which makes it hard to train a prediction model. The primary reason being that the images corresponding to oxygen range between all the values from 2.9 to 3.7 are not available as the boiler conditions change very rapidly during combustion. So, a prediction model will not lead to a generalized model. To overcome this issue, certain crucial oxygen levels from 2.9 to 3.7 of practical importance are identified. Yet, after training, the classification model is not accurate as the oxygen level is not linearly related to boiler temperature. To map the oxygen percentage with the original values, the most frequent oxygen levels that were observed by the boiler were taken, which gave a good dataset that was robust and also can work in real-time. As far as the author is aware, this is the first model which uses classification for finding the oxygen level in the BFG Gas fired boiler.

Table 1: BFG Gas fired Boiler Images at Different Temperature and Oxygen Level (550-625 °C)

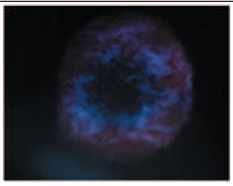
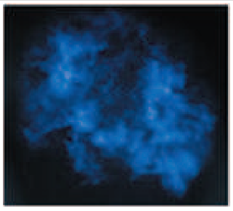
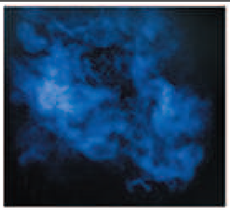
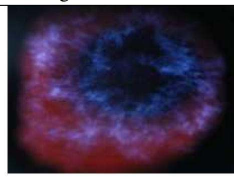
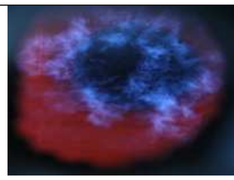
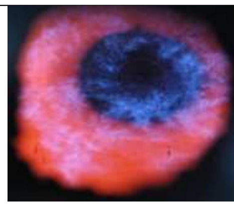
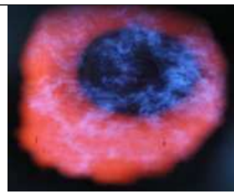
S.No.	Temp.	O_2%	Time	Images
1	550	3.07	3.46 pm	
2	575	3.1	3.43 pm	
3	600	3.15	3.42 pm	
4	625	3.17	3.39 pm	

Table 2: BFG Gas fired Boiler Images at Different Temperature and Oxygen Level (650-725 °C)

S.No.	Temp.	O_2%	Time	Images
5	650	3.24	3.37 pm	
6	675	3.27	3.32 pm	
7	700	3.37	3.24 pm	
8	725	3.39	3.17 pm	

V. Method of Controlling Fuel Combustion

The aim behind the recommended method is to improve the the combustion process automatically, in boilers by persistently monitoring the flue gas oxygen concentration, with the aid of an oxygen sensor, which regulates fuel combustion despite the variations in the quantity of the boiler furnace, incoming gas. As a result, the boiler room system experiences significant energy savings [28].

The information gathered includes a video with the amount of oxygen at different temperatures in the boiler. The video captured was sectioned into proportions and their images were put in separate folders labeled according to the oxygen level. Then data is split into training and testing sets with a split ratio of 75% and 25%, that are respectively used for model training and testing.
Table 1, Table 2 and Table 3 show different boiler images at different temperatures and oxygen levels taken on-site, from a gas-fired boiler at Jayaswals NECO Ltd. Siltara, Raipur. The images were taken using a high end camera over a period of time at various temperatures while also measuring the amount of oxygen present in boiler.
CNN architecture was set up after obtaining labeled images, to assign the images one of the 12 classes depending on the oxygen content. So, given an image, the the network is formulated as a classification task, which classifies the image into one of the classes in accordance with the oxygen level. The low value of loss, as low as 0.04, and the accuracy was 97%, have been obtained after training the model which is a very good measure for classification tasks under test.
The model consists of 7 convolution layers, three max pooling layers and fully connected layers, three in number, to predict the boiler oxygen level.

VI. Data Processing Stage of The CNN Method

Deep learning system followed by a convolutional neural network (CNN) entails local image perception, sharing weights, filters, sub sampling, completely connected layers, and multi-classification. The first step in CNN is the classification, multi-class prediction and flame image analysis for oxygen prediction to produce regional impressions of images. A deep learning algorithm for image categorization that is frequently utilized in hardware implementations is the CNN. A convolution layer, a layer that is wholly connected

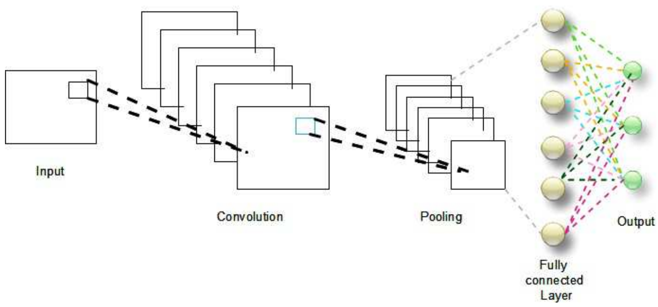
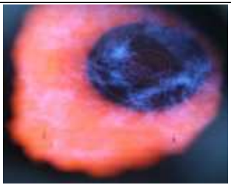
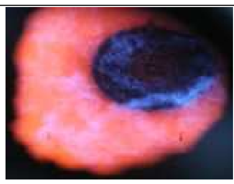
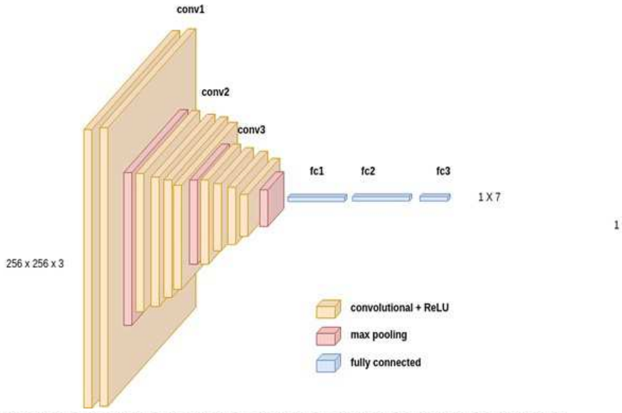


Figure. 4: A Basic CNN

and a pooling layer, are the three types of CNN layers. The input data feature extraction is done in the convolution layer

Table 3: BFG Gas fired Boiler Images at Different Temperature and Oxygen Level (750-812 °C)

S.No.	Temp.	$O_2\%$	Time	Images
9	750	2.7	3.15 pm	
10	775	2.7	3.10 pm	
11	800	2.8	3.07 pm	
12	812	2.9	3.03 pm	




```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1         [-1, 16, 252, 252]           1,216
         MaxPool2d-2         [-1, 16, 126, 126]               0
            Conv2d-3         [-1, 32, 122, 122]          12,832
            Conv2d-4         [-1, 64, 118, 118]          51,264
            Conv2d-5         [-1, 64, 114, 114]         102,464
         MaxPool2d-6           [-1, 64, 57, 57]               0
            Conv2d-7           [-1, 64, 53, 53]         102,464
            Conv2d-8           [-1, 64, 49, 49]         102,464
            Conv2d-9           [-1, 64, 45, 45]         102,464
        MaxPool2d-10           [-1, 64, 22, 22]               0
           Linear-11                  [-1, 120]       3,717,240
           Linear-12                   [-1, 84]          10,164
           Linear-13                   [-1, 12]           1,020
================================================================
Total params: 4,203,592
Trainable params: 4,203,592
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.75
Forward/backward pass size (MB): 31.83
Params size (MB): 16.04
Estimated Total Size (MB): 48.61
```

Figure. 5: CNN Model for Flame Image Monitoring and Layers

[29]. Several filters are used in the feature extraction process.

$$A_j = f(\sum N_i = lI_i * K_{i,j} + B_j) \quad (2)$$

- A_j - a nonlinear activation function
- $K_{i,j}$ - the kernel
- I_i - the input matrix in the kernel
- B_j is the matrix of bias value applied to each element

The result is the convolution layer output matrix. Reducing the dimensions is one of the pooling layer's functions. The size of the output matrix will be shrunk to make the computing process faster. There are several methods for doing so, namely, minimum-pooling, average-pooling, and max-pooling. The pooling layer's 2D matrix is converted to a one dimension matrix, before accessing the layer that is totally connected, every matrix element is placed in an array of single dimension. The categorization process is conducted at the fully linked layer. CNN's architecture is depicted in Figure 4 [16].

The datasets of two kinds of images, namely 'testing' and 'training', are collected in this work. In the convolutional layers several filters are used, convolution is done between parts of input images and filters of a particular size. The CNN uses sub sampling (also known as down sampling) and features are extracted that are translationally invariant, thus reducing complexity of the calculation. Traditional machine learning approaches, on the other hand, require handmade attributes for training, which can be arduous and vulnerable to mistakes. When completely linked, the CNN uses several convolutions and pooling to connect all retrieved features [30]. After all of the images have been extracted, the CNN model is loaded. For consistency, the photos are cropped to uniform dimensions. Once integrated, a dataset meant for training is entailed with a split for validation, using some of the image samples for validation. To boost the efficiency of learning and enhance iteration speed for the CNN model, the pre-processed boiler pictures are saved in cached memory. As seen in the flowchart, a set of data with four classifications was needed for the training data. Once the preprocessing is finished, the data is fed into the CNN architecture to create a classification and prediction model [31, 32]. A colour image of size 256×256,is the network's input, obtained after pre-processing the image and R, G, and B color channel normalizations. When propagated through various layers, the image is downscaled to 252×252, then 126×126, continuing until the wholly connected layers are reached, which classify the image in one of the 12 classes of oxygen level, with the aid of features compiled by convolution and max-pooling layers. The ReLU function is used as activation function, as it aids faster convergence with the aid of the diminishing gradient problem. The Cross Entropy loss function is used to assess loss, which contrasts the target and predicted output,also it back propagates the direct difference between them [32].

In Conv2d-1 an image of shape [-1,3,256,256] is input which is a RGB (3 channel) colour image of resolution 256×256. In the first layer the image is converted to a 16 channel image with dimension of 252×252, the total number of parameters are $16 \times 5 \times 5 \times 3 + 16$ as there are 16 channels in output, 3 channels in input, size of kernel is 5×5 and a bias of 16 is added at the end for 16 output channels. Total comes out to be 1216. Similar situation is for Conv2d-3 where input channels are 16 and image size is 126×126 and output is of 32 channels and size is 122×122 so total parameters are $32 \times 5 \times 5 \times 16 + 32$ leading to a total of 12832. Same is repeated for the rest of the Conv2d layers. Maxpool layers don't have any parameters as they are used to downscale the images. In the linear layer, input to Linear-11 are 64 channels, 22×22 image size giving a flattened output with 1×120 size, and there are 120 biases which make a total of 3,717,240 $(64 \times 22 \times 22 \times 120 + 120)$ parameters. Same calculation applies for Linear-12 where input image is of size, 1×120 and the output is of 1×84 size, which accounts to a total number of 10164 $(120 \times 84 + 84)$ parameters. Similar calculation can be done for the layer, linear-13.

Instead, the online-measured flame photographs can provide

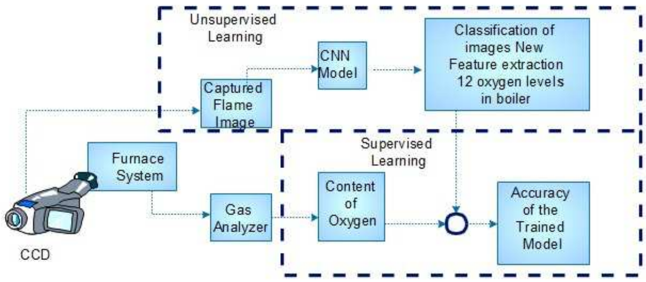


Figure. 6: Oxygen Content prediction in Online Mode using Flame Images of combustion using a CNN Model [9]

substantial information to represent the burning status at the moment. As a result, measures for monitoring and controlling fire have recently drawn increased attention. The pilot-scale combustion furnace's actual data is utilized in this study to illustrate the benefits of the suggested Convolution Neural Network modeling method. There are certain innate connections between the flame pictures and oxygen levels. For instance, physically examining the flame photos can reveal a broad tendency. Additionally, other portions of the flame images, such the gas pipeline and the furnace's black background, are just noise or meaningless information. However, it is challenging to derive a quantitative relationship between oxygen concentrations and visible flame pictures just from human experience. In reality, it is more appealing for significant features to be automatically learned from photographs than to be laboriously constructed by engineers. Therefore, the CNN model employed to immediately build a soft sensor system on the photographs of the flames for the online estimation of the oxygen content. Figure 6 displays the primary conceptual framework for modeling.

A. *Classification of Images*

- **Step 1:**In this step videos of Flame images from gas fired Boiler were acquired where at different temperatures and oxygen levels using high definition camera and then collating into frames.
- **Step 2:**after framing level of oxygen was identified in framed images output with different labels of content of oxygen.
- **Step 3:**A CNN model is developed to classify the images based on 12 Oxygen levels in Gas fired boiler.
- **Step 4:**during training cross entropy loss is used to train model

$$Loss = -\sum_{i=1}^{outputsize} y_i \log \widehat{y_i} \tag{3}$$

VII. Implementation Details and Results

The experiment was conducted in Python 3.6, PyTorch is the framework being used. A free machine learning toolkit called PyTorch is built on the Torch library [33, 34, 35] that is largely used by Meta AI[33, 36] for applications like artificial intelligence and natural language processing [36]. It is an open-source software that is available for free, according to the Modified BSD license. Despite the fact that PyTorch also has a C++ interface, the Python interface has received the majority of development attention [34]. Tesla Autopilot is one of the deep learning applications built on top of PyTorch. Using a CPU with an i9 processor, 128 GB of RAM, and 32 GB of RTX 5000 graphics, Uber completed Pyro Training. The model needed to be trained with 1600 epochs in one day. Parameters and hyper parameters of the models were then selected. Finally, the learning rate was 0.0001, and cross entropy loss and ADAM optimizer were utilized. two high level features are provide by PyTorch followed by Lightning and Catalyst [36]. Tensor computation (similar to NumPy) with significant GPU acceleration (GPU) Using a tape-based automatic differentiation method, deep neural networks. This is

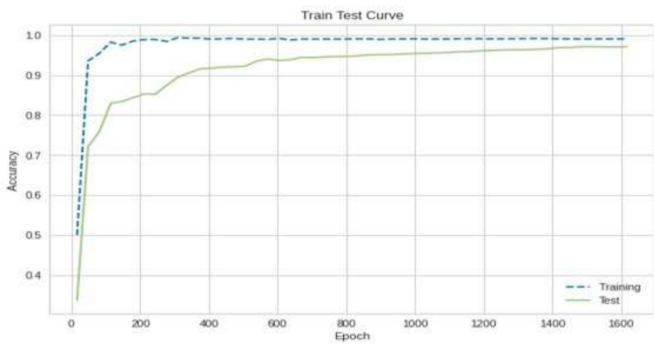


Figure. 7: Train & Test Curve

the curve for training and while training accuracy was around 99 percent, testing accuracy is 97 percent which gives a clear idea that model is performing very well on unseen data and also the model is not over fitting and generalizing well.

A. *Confusion Matrix*

An easy approach to see how well a prediction model is performing is to create a confusion matrix. The amount of predictions made by the model, whether properly or erroneously, is indicated by each item in a confusion matrix. The samples from our test set are labelled on the y-axis with their genuine labels, and the x-axis displays the predicted labels. If every test sample was correctly classified for every class or group

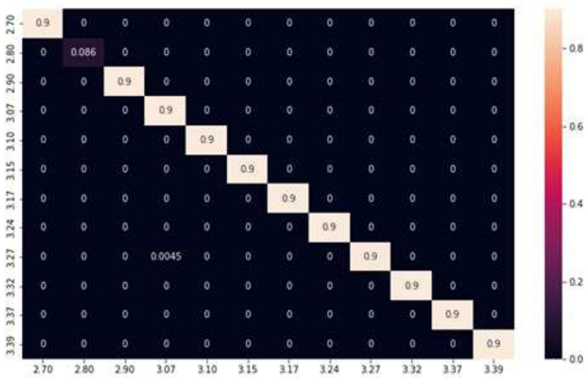


Figure. 8: Confusion Matrix of Output

that was supplied, the ideal classifier would produce a confusion matrix with values only on the diagonal [37]. The upper left box in the current example has a value of 0.9 inside, but the next 11 boxes in a column have a value of 0. This indicates that the model successfully classified each test sample. On the other hand, it can be observed from the fourth column, which represents the 3.07 group, that it correctly classified 90 percent of the test samples and missed 0.045 test samples that were incorrectly classified.

B. Other Metrics

The performance of the proposed model is quantified with F1-Score, recall, precision, accuracy, and Receiver Operating Characteristic (ROC) curve. Note that for evaluation, the lower the measurements, the better and the ability of CNN. Their definitions are as follows:

$$\begin{aligned} Precision &= \frac{T_P}{(T_P + F_P)} = 0.4264 \\ Recall &= \frac{T_P}{(T_P + F_N)} = 0.0181 \\ (F1 - Score) &= \frac{(2(Recall)(Precision))}{(Recall + Precision)} = 0.0347 \\ Accuracy &= \frac{(T_P + T_N)}{(T_P + T_N + F_P + F_N)} = 0.98 \end{aligned} \tag{4}$$

Where, the outcomes used are as follows:

- T_P - true positive
- T_N - true negative
- F_P - false positive
- F_N - false negative

VIII. Conclusions and Future Scope

Combustion is essential part in a Gas fired boiler and reducing loss is a ubiquitous problem. An accurate oxygen content prediction is very essential. In this study, a CNN model is suggested to address such problems by forecasting the oxygen content of flue gases. Three aspects of the algorithm are examined: feature selection, data pre-processing, and data analysis modeling. Important features are usage of convolutional ReLU, max Pooling and fully connected filters. As compared to DBN Method accurate data prediction is carried out using CNN Technique. CNN model is applied for oxygen prediction in a BFG gas fired boiler in a power plant by accumulating 12 different images and then applying CNN model for prediction. The accuracy found was up to 97%, and post training loss was 0.04. The effectiveness and strength of the modeling strategy proposed and attribute selection techniques are depicted by the end results. The suggested algorithm can be used to develop a predictive control application in the future. Also ensemble model can be used which adds on other parameters and can make a more precise prediction model.

Data Availability Statement

The datasets generated and analyzed during the current study are available from the corresponding author on reasonable request.

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